# The information content of earnings announcements in Denmark

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## Abstract

**Purpose** – The purpose of this paper is to examine the reaction to earnings announcements in a small stock market.

**Design/methodology/approach** – The paper uses the traditional event study method to examine the information content of annual earnings announcements in the small Danish stock market from 1999-2004.

**Findings** – The paper finds abnormal volatility in the days surrounding the announcements, indicating that they contain relevant information for the stock market. The abnormal volatility persists several days after the announcement, suggesting that the information environment of this small stock market works to decrease the speed of adjustment. In addition to this sign of inefficiency, the paper finds significant positive abnormal returns accompanying the announcements. These results are robust across various methodologies. Surprisingly, the paper finds a positive correlation between the information content and predisclosure information. This contradicts previous studies, and it is interpreted as evidence of a low level of pre-announcement information. Confirming the results of similar studies, the paper finds that unexpected earnings are best proxied using a model based on consensus analyst forecasts.

**Originality/value** – This paper contributes to the existing literature by analyzing the information content of earnings announcements in a small stock market with accounting standards that are congruent with the International Accounting Standards.

**Keywords** Earnings, Financial forecasting, Denmark

**Paper type** Research paper

## 1. Introduction

One of the most compelling and intriguing research questions of our time is how information is reflected in the price of stocks. In this paper we provide new evidence in this area by analyzing Danish earnings announcements (EAs). First, we examine whether the Danish stock market reacts to EAs in an efficient manner that is consistent with the EAs containing relevant information. We then attempt to explain the market's reaction using the level of predisclosure information and amount of surprise contained in the EA.

This study contributes to the existing literature in two respects. First, we analyze the information content of EAs in a small stock market where the accounting standards are congruent with the International Accounting Standards (IAS). The manner in which small stock markets react to earnings announcements is interesting,

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since there are several aspects where it is likely that small and large stock markets differ with respect to their information environment. With regard to pre-announcement information it can be argued that the smaller size leads to a less developed market with less investor sophistication and therefore less pre-announcement information. On the other hand, one could argue that the smaller size leads to a more transparent market with more pre-announcement information. Additionally, it is possible that the speed with which the new information is incorporated into prices is affected by the size of the stock market. Again, predictions regarding both a decrease and an increase in the speed of adjustment can be set forth. Therefore in both cases the question of which effect is the dominant one becomes an empirical issue.

The information content of EAs in a small stock market has previously been studied in Kallunki (1996) in the context of the Finnish stock market. However, there are two rather unique institutional features of the Finnish stock market that make it a less suitable candidate for isolating the effect of stock market size on the information content of EAs. First, as mentioned in Kallunki (1996), Finnish accounting standards are very different from the IAS. Secondly, as also noted by Kallunki (1996), short-selling is not possible in the Finnish stock market, and this has implications for the market's ability to adjust to negative EAs. In contrast, the Danish stock market does not share any of these peculiar features with the Finnish stock market, hence making the Danish stock market more suitable for isolating the effect of stock market size on the information content of EAs. Thus, firstly, Danish accounting standards are congruent with the IAS. Secondly, short-selling is allowed on the Danish stock market, hence allowing investors to adjust to negative EAs. Analyzing the information content of Danish EAs therefore provides for a cleaner examination of the manner in which small stock markets react to EAs.

Second, an in depth analysis of the information content of Danish EAs is interesting, given that Plenborg (1998) in his association study found evidence indicating that Danish earnings were more informative than US earnings. He attributed this finding to a larger degree of flexibility in the Danish accounting system compared to the US. He therefore suggested that his findings contradicted the idea of the then current FASB agenda which emphasized the comprehensive income statement. However, his findings of a higher degree of association between returns and earnings changes can also be interpreted as indicating that the level of pre-announcement information in the Danish stock market is lower than in the US. Indeed, some of his sensitivity analyses seem to support this explanation. We therefore take a closer look at the stock market's reaction to the announcement of Danish EAs, and at the extent to which the reaction can be explained by different measures of predisclosure information and unexpected earnings. While the Danish papers by Sørensen (1982) and Lønroth *et al.* (2000) present results on the information content of Danish EAs, the present paper is the first to offer a coherent explanation of the market reaction to Danish EAs. We therefore contribute to the existing literature by presenting evidence that sheds light on the explanation behind the interesting association study findings of Plenborg (1998).

Our results indicate that Danish EAs do contain new and relevant information for the stock market. This is similar to the findings of previous studies on large stock markets. However, the Danish stock market is slow to absorb the new information, and in fact the reaction persists for up to several days after the announcement. This indicates that the information environment in this small stock market works to

decrease the speed of adjustment. Additionally, we find significantly positive abnormal returns around the announcement. These two findings indicate that the Danish stock market does not react efficiently to EAs. Opposing theory and previous empirical work we also find a positive correlation between the information content of EAs and proxies for predisclosure information. We interpret our results as indicating that the level of predisclosure information is low in Denmark. Our evidence therefore indicates that the dominant effect of the smaller size of the stock market on the information environment is to lead to less pre-announcement information, not more. Additionally, these results are interesting given the previously mentioned findings in Plenborg (1998) of a higher degree of association between stock returns and unexpected earnings in Denmark compared to the US. While Plenborg (1998) suggested that this was due to superior Danish accounting standards, our results support the notion that the higher degree of association simply reflects a lower level of predisclosure information in Denmark. Finally, we find that using consensus analyst forecasts as proxies for the market's expectations of earnings provides a better model for unexpected earnings than a naive model that assumes that earnings follow a random walk.

The next section gives a brief overview of previous literature. Hereafter, we provide a brief description of the Danish stock market. Following this we introduce the methodology used in this study. The fifth section describes our data. In the sixth section we present the results. Our conclusion is given in the seventh section.

## 2. Previous literature

### *2.1 Market efficiency*

The notion of stock market efficiency, first introduced by Fama (1965), has played a central role in both theoretical and empirical work on the reflection of information in stock prices. As defined by Fama (1970), a stock market is efficient if prices always fully reflect available information. Information is divided into three subsets, distinguishing between weak, semi-strong and strong form efficiency with respect to historical prices, publicly available information, and private information, respectively. A related strand of literature, reviewed in Verrecchia (2001), has dealt with the theoretical modeling of how the disclosure of information affects investors as reflected in stock prices and trading volume. One interesting insight from this literature is the revelation in Grossman and Stiglitz (1980) that prices can only fully reflect costless information, since there must be a return to acquiring information at a cost, otherwise there will be no information acquisition. This insight indeed led to a revised definition of efficiency in Fama (1991), where two versions of the hypothesis that security prices fully reflect all available information are given. The strong version stipulates that information and trading costs are always zero, while the weaker version states that prices should reflect information to the point where the marginal benefits of acting on information do not exceed the cost. As noted in Ball (1994) this in essence involves a reclassification from the three earlier and more statistically-based information subsets to subsets based on the cost of information. Empirical work has to a large extent supported the efficiency hypothesis, although several anomalies have been uncovered (see the reviews by Fama (1991) and Kothari (2001)), e.g. the post announcement drift, which concerns the tendency for stock prices to continue to drift after information disclosures.

*2.2 Disclosure*

While the efficiency hypothesis avoids the issue of how individuals process information and implicitly assumes homogeneous information, the disclosure literature has provided additional insight by more explicitly modeling this process and allowing for heterogeneous information. Indeed, Kim and Verrecchia (1997) show that empirical observations regarding the behavior of trading volume and price around announcements can only be supported by a theoretical model that allows for both heterogeneous private information about the value of the firm (pre-announcement information) and diverse investor interpretation of the disclosure due to heterogeneous event-period information. Their results show that the change in stock price depends on the average pre-announcement and event-period information. Underscoring this result, Liang (2003) finds a significant positive relationship between the post-earnings announcement drift and heterogeneous information. Finally, the theoretical paper by Holthausen and Verrecchia (1988) suggests that the stock market's reaction should be inversely related to the level of predisclosure information, which is referred to as the predisclosure information hypothesis. These theoretical and empirical studies therefore indicate that the information environment plays a central role in the stock market's reaction to information disclosures.

*2.3 Empirical evidence on earnings announcements*

The empirical literature on the stock market's reaction to information disclosures is vast and covers such diverse information as stock splits and changes in inventory accounting. An area that has received particular focus is the question of how earnings and stock market prices are related. This area of the literature began with the seminal work by Beaver (1968) and Ball and Brown (1968). These two studies and those following them can roughly be grouped into two categories: association studies and event studies. While event studies attempt to ascertain the information content of EAs by examining the market reaction in a short window surrounding the announcement, association studies are concerned with the long-term association between earnings and stock prices. Although many studies have been conducted in the US on both topics, most of the sparse European evidence has concentrated on association studies and pertains mostly to the UK, as noted in the review by Dumontier and Raffournier (2002).

A list of the European evidence regarding the market's reaction to EAs that has been published in English is therefore fairly short and covers only a few countries. Studies have been conducted in the UK by Firth (1981), Pope and Inyangete (1992), Rippington and Taffler (1995), and Elsharkawy and Garrod (1996), in Finland by Kallunki (1996), in Spain by Pellicer and Rees (1999), and in France by Gajewski and Quéré (2001). The evidence presented in these articles is generally consistent with the results of US studies. Earnings announcements do appear to contain information that is relevant to the stock market, and for the most part it appears that the stock market reacts efficiently to this information. As with other types of information disclosures, an anomaly has been observed in the post-earnings announcement drift, which is the tendency for the stock price to drift after the EA. However, the evidence presented in these articles cannot be generalized to other European countries, due to the varying accounting standards and information environments (see Alford *et al.* (1993)) across countries in Europe. At the same time, these differences in information environments make results from other countries interesting, since theory indicates that the

information environment has an impact on the manner with which stock markets react to information.

As Dumontier and Raffournier (2002) also note, there is the possibility that studies have been conducted in other countries but not published in English. This is indeed the case in Denmark, where two previous studies published in Danish have examined the information content of Danish EAs. While Sørensen (1982) used weekly data, Lønroth *et al.* (2000) conducted a study using daily data. As argued, however, it seems that the results of such studies of different markets with different information environments should be of interest to a much broader audience.

While the above studies examined the information content of EAs and whether or not the market reacted efficiently, several studies have also examined how the level of predisclosure information impacts the market reaction to EAs. The predisclosure information hypothesis only pertains to the size of the market's reaction, and provides no guidance as to the expected direction of the reaction. A direct examination of the relationship between predisclosure information and the market reaction therefore provides no insight on the validity of this hypothesis. Instead, the empirical work has used two different approaches to test the predisclosure information hypothesis. The first of these directly examines the relationship between a measure of information content for each EA and proxies for predisclosure information. The second approach examines how predisclosure information affects the earnings response coeffcient (ERC). The ERC measures the per unit change in price per dollar of earnings surprise and is found by regressing abnormal returns on unexpected earnings. Christensen *et al.* (2004) use this methodology to examine the predisclosure information hypothesis by regressing abnormal returns on unexpected earnings and interaction terms between unexpected earnings and proxies for predisclosure information. Although similar, there is a subtle difference between these two methods. In the latter approach, the hypothesized inverse relationship between the market reaction and predisclosure information is assumed to arise because the market reacts less to a given level of earnings surprise for firms with more predisclosure information. As Kross and Schroeder (1988) argue, this effect can arise, because the greater availability of other sources of information leads investors to rely less on current earnings when forecasting future cash flows. In addition to this effect, the first approach also captures the possible effect that there is less surprise in EAs from firms with a greater level of predisclosure information.

Since the amount of predisclosure information cannot be observed directly, empirical work has tested this notion using proxies for the level of predisclosure information. Although numerous proxies have been used, two appear frequently in the literature. The first of these is firm size. Use of this proxy was initiated by Atiase (1985), who put forth the firm size-related differential information hypothesis. This hypothesis proposes that the amount of predisclosure information related to the market is an increasing function of firm size. The unexpected information conveyed to the market with the EA will therefore be inversely related to firm size. The second frequently used proxy is the number of analysts following a firm. Indeed, Dempsey (1989) argues that the number of analysts following a firm provides a better proxy for predisclosure information than firm size, since it reflects incentives for information gathering in addition to firm size.

This empirical work has largely found evidence in support of the proposed inverse relationship between the market reaction to EAs and predisclosure information regardless of the approach and proxies used (i.e. Atiase, 1985, Lobo and Mahmoud, 1989, Dempsey, 1989, Shores, 1990, Pope and Inyangete, 1992 and Christensen *et al.*, 2004).

## 3. The Danish stock market

The Copenhagen Stock Exchange (CSE) constitutes the Danish stock market. During our period of interest, 1999-2004, the market capitalization of listed companies rose from 629.3 billion DKK[1] ultimo 1998 to 896.1 billion DKK ultimo 2000, to fall to a level of 564.1 ultimo 2002, and hereafter rise to a level of 856 billion DKK ultimo 2004. The Danish stock market is concentrated, in that the KFX-index, which is comprised of the 20 stocks traded most actively in the preceding six month period, accounts for 70-80 percent of this value. The total turnover of listed companies rose from 260 billion DKK in 1999 to 455 billion DKK in 2000, to fall to 391 billion DKK in 2002, and finally rise to 593 billion DKK in 2004. Again, the KFX-index accounts for a large share of this, approximately 80-90 percent, indicating the infrequent (thin) trading of many stocks listed on the CSE.

All companies listed on the Danish stock exchange are required to publicize annual earnings announcements. These are short versions of the annual report that are made public before the annual report, and at the latest on the same day. They contain the results for the completed fiscal year, a short description of the preceding year, and expectations regarding the future. Since the Danish accounting standards went unchanged until 2002, Plenborg (1998) provides a useful comparison of the Danish and US accounting standards that covers the first part of our period of interest.

## 4. Methodology

The methodology used in this study is the standard event study methodology, see for example Campbell *et al.* (1997). This method builds on the assumption that it is possible to isolate the part of a stock's return which concerns a particular event. This is done by using a model to estimate the normal return, i.e. the stock's return if the event had not happened. The abnormal return, which the event generates, is found as the difference between the actual return and the estimated normal return. The information content of an event is then examined by evaluating the abnormal returns around the announcement date. In this study the EA date is set to day 0. The parameters of the model for the normal returns are estimated in an estimation period covering $(-185; -6)$, while the abnormal returns are examined in the 11-day event window $(-5{:}5)$.

There are several models that can be used to estimate the normal returns. This study uses the market model, which Brown and Warner (1985) find is well-specified under a variety of conditions when using daily returns. The market model for each firm is given as:

$$R_{j,t} = \alpha_j + \beta_j R_{m,t} + \varepsilon_{j,t}, \tag{1}$$

where $R_{j,t}$ and $R_{m,t}$ denote the returns to stock $j$ and the market portfolio on day $t$, respectively. The market model divides the return of a stock into two parts: one part that is determined by the market's returns, i.e. market determined $\alpha_j + \beta_j R_{m,t}$, and

another that is company specific and influenced by information about the company, $\varepsilon_{j,t}$. When the market model is used in an event study, the normal return becomes the market determined, while the abnormal return is the company specific. An implicit assumption in event studies using the market model is therefore that no information about the company other than the type examined is made public in the event window. Since previous research indicates that results of short-horizon event studies such as this are not affected by the model chosen to estimate normal returns (see for example Brown and Warner (1985) and Kothari and Warner (2004)), we will only measure normal returns using the market model.

The abnormal return in the event window, $AR_{j,t}$, for the $j$th EA at day $t$ is therefore given as:

$$AR_{j,t} = R_{j,t} - \hat{\alpha}_j - \hat{\beta}_j R_{m,t}.$$

The abnormal returns in the estimation period are directly given as the residuals from the estimation of the market model. The variance of these residuals is calculated as:

$$\sigma_j^2 = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_{j,t}^2}{T-2},$$

where $T$ is the length of the estimation period. If we assume that the variance of the abnormal returns is equal in the estimation period and event window, then the variance-covariance matrix for the ARs can be calculated from:

$$\hat{V}_j = I\hat{\sigma}_j^2 + X_j^* \left(X' X_j\right) X_j^{*\prime} \hat{\sigma}_j^2, \tag{2}$$

which takes into account the sampling error in $\hat{\alpha}$ and $\hat{\beta}$. This formula is in vector notation, where $X_j$ is a matrix with a vector of ones in the first column and a vector with the market returns in the estimation period in the second column. $X^*/j$ is composed of a vector of ones and a vector of market returns in the event window. $\hat{\sigma}^2/j$ is defined as before. We now take a closer look at how the market model is estimated.

*4.1 Estimation of the market model*

A market model is estimated for each firm using ordinary least squares. One problem in this estimation is that the Danish stock market, like any small stock market, is characterized by having many stocks that are traded infrequently, i.e. thin trading. There are two aspects to this problem. The first is that the registered closing stock prices can be from transactions made earlier in the day. It is a well known problem that this non-synchronous trading results in biased estimates of the market model parameters (see for example Brown and Warner (1985)). However, several studies have shown that the results of event studies are not changed noticeably, when alternative unbiased estimates are used (see Brown and Warner, 1985 and Dyckman *et al.*, 1984). This aspect will therefore not be pursued further in this study.

The second aspect is that there are days where no trading has occurred resulting in no registered stock price. Generally two methods are used to handle this problem. One is to use fairly arbitrary restrictions on the trading frequency to remove stocks from the sample that are traded infrequently. This, however, results in small samples that are not representative of the entire stock market. The second method is to use a

procedure to allocate the multiperiod return on a given trading day over the previous interval, where the stock was not traded. Maynes and Rumsey (1993) investigate three such procedures. The first is the "lumped" procedure, which allocates the entire return to the day the stock is traded, while the return on days with no trade is set to zero. The uniform. procedure distributes the multiperiod return from a day of trade equally over the multiperiod interval. The last procedure is the "trade-to-trade" which directly uses the multiperiod returns instead of allocating them over the interval. To investigate the effect of these two methods on the results, we will use two different sets of trading restrictions to create two data sets and then generate results for these data sets using all three return allocation procedures.

Compared to the lumped and uniform procedures, the trade-to-trade procedure requires a number of extensions. Since the trade-to-trade procedure uses multiperiod returns, matching multiperiod returns must be generated for the market index. Additionally, a trade-to-trade version of the market model must be used. Maynes and Rumsey (1993) assume an underlying stationary one-day return generating process and derive the trade-to-trade market model as:

$$R_{j,n_t} = \alpha_j n_t + \beta_j R_{m,n_t} + \sum_{s=0}^{n_t-1} \varepsilon_{j,t-s},$$

where $n_t$ is the period length of day $t$'s multiperiod return, while $R_{j,n_t}$ and $R_{m,n_t}$ are multiperiod returns for stock $j$ and the market index, respectively. The residuals in the model are heteroskedastic with variance equal to $n_t\sigma^2/j$, which makes it necessary to divide the data with the square root of the multiperiod return length, when estimating the model's parameters. With the trade-to-trade procedure abnormal returns in the estimation period are calculated as:

$$\hat{\varepsilon}_{j,n_t} = R_{j,n_t} - \hat{\alpha}_j n_t - \hat{\beta}_j R_{m,n_t},$$

while the variance of the abnormal returns $\hat{\sigma}^2/j$ is calculated from:

$$\hat{\sigma}_j^2 = \frac{\sum_{t=1}^{T_j} \left(\frac{\hat{\varepsilon}_{j,n_t}}{\sqrt{n_t}}\right)^2}{T_j - 2},$$

where $T_j$ is the number of observations in the estimation period for the $j$th EA. The abnormal return in the event window $AR_{j,t}$ for the $j$th EA at day $t$ is then:

$$AR_{j,t} = R_{j,n_t} - \hat{\alpha}_j n_t - \hat{\beta}_j R_{m,n_t}.$$

Finally, we note that when trade-to-trade returns are generated for the estimation period, uniform returns will be used in the event window to allow for the conduction of tests of information content. Therefore the above formula for $AR$s in effect has $n_t = 1$.

With the basic methodology in place we will first take a closer look at how the tests for information content are constructed. The last subsection will introduce the methodology used to examine the relationship between information content and proxies for predisclosure information and unexpected earnings.

*4.2 Information content of earnings announcements*

The abnormal returns can be used to answer the following questions:

(1) Is there an information content in the EAs?

(2) If there is an information content, then how quickly does the market react and adjust to the new information?

(3) Does the market on average have realistic expectations of the EAs?

How the first two questions are examined is described in the.rst subsection, while the next deals with the last question.

*4.2.1 Tests of information content and market adjustment speed.* In order to answer the first two questions, the average abnormal returns across stocks can be calculated. However, since positive and negative abnormal returns will cancel each other out, this calculation will result in a loss of part of the information content. One common method to handle this is to use a model for unexpected earnings to divide the abnormal returns into a positive and negative group. This, however, results in a joint test of information content and the model of unexpected earnings, and is therefore undesirable here. Instead we compare the squared abnormal returns with the variance $\hat{V}$ from (2) using the following test statistic from Patell (1976):

$$Z_{U_t} = \frac{\sum_{j=1}^{N} (U_{j,t} - 1)}{\left[\sum_{j=1}^{N} \frac{2(T_j - 3)}{T_j - 6}\right]^{\frac{1}{2}}} \overset{a}{\sim} N(0,1), \tag{3}$$

where:

$$U_{j,t} = \frac{AR_{j,t}^2}{\hat{V}_{j,t}} \cdot \frac{T_j - 4}{T_j - 2}, \tag{4}$$

and $\hat{V}_{j,t}$ denotes the variance for EA $j$ from the variance-covariance matrix $\hat{V}_j$ at time $t$ in the event window. The test statistic $Z_{U_t}$ can be interpreted as a test of the previous assumption that the variance of the abnormal returns is equal in the estimation period and event window if the hypothesis $E[AR_{j,t}] = 0$ is true.

If the EAs have an information content, then this will lead to an adjustment of the stock price, which in turn will generate large squared average abnormal returns. Information content of EAs is therefore proven, when the test statistic assumes significant large values. The speed of adjustment of the market is examined, by looking at how many and which days have significant values of the test statistic. If the market is efficient, then it should adjust quickly.

*4.2.2 Tests regarding the average expectations.* If it is found that the EAs have information content, then we can test whether the market on average has realistic expectations of the information in the announcements. Large positive (negative) abnormal returns signal that the EAs were over (under) the market's expectations. We can therefore test the market's average expectations by examining whether the average abnormal returns at a given point in time in the event window are significantly

different from zero. Such a test must, however, take into account that the finding of information content can carefully be interpreted as an indication that the variance of the abnormal returns in the estimation period and event window is different. Boehmer *et al.* (1991) find that even a small increase in the variance in the event window results in the most common tests often rejecting the null hypothesis of no average abnormal return, when this hypothesis is in fact true. Additionally, Kallunki (1997) finds that when thin trading in the event window necessitates using procedures such as the uniform, it is important to take increased variance into account by using the test statistic from Boehmer *et al.* (1991). When the event induces an increased variance, Boehmer *et al.* (1991) recommend the following test statistic:

$$J_t = \frac{\frac{1}{N}\sum_{j=1}^{N} SAR_{j,t}}{\sqrt{\frac{1}{N(N-1)}\sum_{j=1}^{N}\left(SAR_{j,t} - \frac{1}{N}\sum_{j=1}^{N} SAR_{j,t}\right)^2}} \overset{a}{\sim} N(0,1), \tag{5}$$

where $SAR_{j,t} = ARL_{j,t}/\sqrt{\hat{V}_{j,t}}$ and $\sqrt{\hat{V}_{j,t}}$ is the standard error for EA $j$ at time $t$ in the event window from the variance-covariance matrix for the abnormal returns in the event window.

If this test rejects that the market on average had realistic expectations, then it has been possible to earn an above normal profit in the period by utilizing mechanical trading rules, in which case the market is not efficient.

There is a potential problem with the above test statistics. Implicitly they assume cross-sectional independence between the abnormal returns and therefore set the covariances between abnormal returns to zero. Since many of the EAs are announced in March, there is some overlap in the event windows of the EAs. This will induce nonzero covariances between the abnormal returns in the cross-section, thereby violating the implicit assumption. However, simulation studies by Brown and Warner (1985) and Boehmer *et al.* (1991) indicate that event clustering does not invalidate inferences made with the above test statistics in short-horizon event studies such as this. Hence we choose not to pursue this potential problem further.

### *4.3 Explaining information content*

It is clear that in an efficient and rational market any information content found should be explained by the component of surprise in the earnings announcement. We will test this notion using two approaches commonly found in the literature. The first approach is to relate the level of predisclosure information to firm characteristics. EAs from firms with a high level of predisclosure information should only contain a small component of surprise and the abnormal returns for these firms should therefore be small. In the second approach we attempt to directly measure the component of surprise by using a proxy for the market's expectations of earnings.

*4.3.1 Predisclosure information.* Theoretical work has indicated that the information environment has an impact on the stock market's reaction to EAs. We will examine the relationship between predisclosure information and information content in EAs using two common proxies for the amount of predisclosure information. The first of these is firm size, which we measure as both the market value of equity the

day before the event window and the natural logarithm of this market value. The second proxy is the number of analysts following a firm taken from the International Brokerage Estimate System (IBES)[2]. For EAs with no IBES data we assume that zero analysts follow the firm.

As mentioned in the review of previous literature, empirical work has used two different approaches to test the predisclosure information hypothesis. We will use both approaches in our study of the effect of predisclosure information. The first approach directly examines the relationship between a measure of information content for each EA and proxies for predisclosure information. This is commonly done using a measure such as $U_{j,t}$, from (4) as the dependent variable in a regression on proxies for predisclosure information (e.g. Atiase, 1985 and Pope and Inyangete, 1992). In order to place as few restrictions as possible on the relationship between information content and predisclosure information, we will test the hypothesis by directly examining the correlation between our measure of information content for each EA, $U_{j,t}$, from (4) and our proxies for predisclosure information. This will be done using both the Pearson-Product Moment (PPM) correlation coefficient, which assumes that the variables are bivariate normally distributed, and the nonparametric test based on the Spearman Rank Order (SRO) correlation coefficient (see Kendall and Gibbons, 1990). The SRO correlation coefficient requires no distributional assumptions, but retains an efficiency of 91.2 percent if the distribution is in fact bivariate normal (see Hotelling and Pabst, 1936). Additionally, we will also follow the second approach and regress abnormal returns on measures of unexpected earnings, which we define in the next section, and interaction effects between unexpected earnings and proxies for predisclosure information.

*4.3.2 Unexpected earnings*. Since it is natural to assume that the abnormal returns can be explained by the unexpected earnings, i.e. the difference between the actual earnings and the market's expectations of these, this will be investigated here. This, however, presents the problem of choosing a proxy for the market's expectations, since these are not known. There are many possible proxies that generally can be categorized as either time-series models or analyst forecast models. Previous studies have attempted to uncover the best proxy by examining the association between abnormal returns and unexpected earnings from the opposite angle, i.e. the best proxy is the unexpected earnings measure that has the highest association with abnormal returns. Using this method many studies have found that models using analysts' forecasts provide the best proxy (for example Fried and Givoly, 1982 and Brown *et al.*, 1987a), while others have found the best proxy to be based on time-series models (for example Hughes and Ricks, 1987 and O'Brien, 1988). These results are all on US data and do not provide consensus as to which measure provides the best proxy.

This study will therefore provide evidence for Denmark by using the same methodology for two different models of unexpected earnings. One is a naive time-series model which predicts that this year's earnings will be the same as last year's, i.e. earnings follow a random walk. The other utilizes consensus analyst forecasts from IBES as estimates of the market's expectation of earnings. Generally, our measure of unexpected earnings (UE) based on earnings per share (eps) can be written as:

$$UE = \frac{actual\ eps - forecast\ eps}{deflator}.$$

The IBES estimates are forecasts of eps excluding discontinued operations, extra-ordinary charges, and other non-operating items. The measure of actual eps

must therefore correspond to this definition. The I/B/E/S database provides such an adjusted measure of actual eps, which we will use in calculating unexpected earnings for the IBES model. However, Philbrick and Ricks (1991) find several problems with the actual eps data from I/B/E/S and conclude that the choice of data source for actual eps is more crucial than the corresponding choice for analysts' forecasts. We have therefore also obtained actual eps data from Account Data, which is a database maintained by the Copenhagen Business School that contains information from the financial statements of Danish companies. Account Data provides a measure of actual eps that is adjusted so that it is before extraordinary items, and it is this measure that we use. Both sources of actual eps data will also be used in the naive model.

A second choice involved in calculating the measure of unexpected earnings concerns which deflator to use. Since the choice of deflator varies across studies, this study will use three different deflators commonly found in the literature. The first of these is $deflator = 1$, which corresponds to using no deflator. The second deflator that we will use is $|forecast\ eps|$. The last deflator used is the market value of equity at the beginning of the period, which Christie (1987) concludes is the correct deflator to use in studies of this type.

To avoid placing excessive restrictions on the relationship between unexpected earnings generated from the models and abnormal returns cumulated over the event window, CARs, the association will first be tested using tests of the correlation coefficient. Again this will be done using tests based on both the PPM and SRO correlation coefficients. Additionally, we will also conduct a multivariate analysis by regressing CARs on measures of unexpected earnings. This allows us to examine whether the different measures have incremental explanatory power over each other. As mentioned, we will also include interaction effects between the unexpected earnings and proxies for predisclosure information. Finally, controls for industry and time are included in these regressions as well.

## 5. Data

The sample is constructed from.rms listed on the CSE from 1999 to 2004. To ensure that the EAs are fairly congruent in their information content, we are only interested in companies that report earnings in accordance with the Danish Companies Account Act. This excludes banks and insurance companies from the study. The EA dates for the above companies in the period 1999 to 2004 are extracted from Stockwise, which is CSE's database of stock exchange announcements. This resulted in a sample consisting of 215 companies and 1,052 EAs. In order to include an EA in the study, we require that the company's stock is listed on the CSE the first day of the estimation period for a given EA. This reduces the sample to 214 companies and 1,034 EAs.

The Danish stock market is characterized by having many stocks that are traded infrequently. In event studies of stock markets with thin trading it is common practice to place certain demands on the trading frequency of a stock in order for it to be included in the study. As mentioned before, we will use two different sets of restrictions. Our first relaxed set of "minimal" restrictions requires that the stock is traded in at least 1/3 of the estimation period and either the last day of the event window or at least one day in the period after. This reduces the sample to 626 EAs. The second set of "strict" restrictions requires that the stock is traded in 1/3 of the

estimation period, every day in the event window, and the day before the event window. This set of restrictions reduces the sample to 324 EAs.

In addition to the dates of the EAs, the data material consists of the individual stock's total return index, market value of equity, and turnover by volume collected from Datastream. The total return indices are corrected for dividends and any changes in the capital structure, and the daily returns of the stocks are therefore calculated directly as differences in logarithmic price indices. The market index is collected from the CSE and is the exchange's all-share index, KAX. The analysts' forecasts used in the study are consensus forecasts from IBES. These forecasts are obtained from the I/B/E/S database along with the actual annual earnings. As mentioned previously, the actual annual earnings are also obtained from Account Data.

## 6. Results

This section presents the results of the study. In the first subsection, the results of the tests for information content are presented. The next and last subsection covers the results from the two approaches used to explain the information content of EAs, i.e. proxies for predisclosure information and unexpected earnings.

First, however, we present descriptive statistics for the abnormal returns from the two data sets constructed using the strict and minimal trading frequency restrictions. We only present descriptive statistics for abnormal returns generated using the trade-to-trade return allocation procedure, since results for the lumped and uniform return allocation procedures are similar (see Table I).

From the table we see that the distribution of the abnormal returns is skewed and leptokurtic. Indeed, the Jarque-Bera test clearly rejects the hypothesis that the abnormal returns follow a normal distribution. As expected the deviation from the normal distribution seems to be even larger when the trading frequency restrictions are relaxed to include the less frequently traded stocks. This is in accordance with the finding of Campbell and Wasley (1993) that the degree of nonnormality in abnormal returns from NASDAQ securities is greater than that in NYSE/ASE securities. This evidence of nonnormality poses a potential problem for the tests of information content, since they assume that the abnormal returns follow a normal distribution. Hence, we will later examine the robustness of our results from the parametric test statistics for information content by also conducting nonparametric tests.

### *6.1 Information content of earnings announcements*

As previously mentioned, whether or not EAs have information content can be tested using average squared abnormal returns in the test statistic $Z_{U_t}$ from (3). This test statistic is shown in Table II.

The table illustrates without a doubt that the EAs contain information. The market experiences large price reactions on the day of the announcement and the day after. We can therefore conclude that the EAs contain relevant and unexpected information for the market. However, there are also significant values of the test statistic on other days than these two. The market reaction to the EAs therefore seems to be rather slow, indicating market inefficiency. Indeed, the market reaction is slower than in most similar studies in the US and UK. The evidence from Denmark therefore indicates that the information environment of this small stock market is such that it slows the speed with which the market adjusts to EAs. Finally, these results are robust in the sense that

**Table I.**
Descriptive statistics for abnormal returns

| Event day | Min. | Max. | Mean | Standard deviation | Skewness | Excess kurtosis | Jarque-Bera |
|---|---|---|---|---|---|---|---|
| *Panel A. Strict restrictions* | | | | | | | |
| −5 | −0.1063 | 0.1909 | −0.0003 | 0.0294 | 1.3200 | 10.4589 | 1,561.1260* |
| −4 | −0.1425 | 0.1037 | 0.0011 | 0.0258 | −0.2308 | 4.2547 | 245.7330* |
| −3 | −0.1531 | 0.2136 | 0.0038 | 0.0330 | 1.3110 | 8.8564 | 1,144.5900* |
| −2 | −0.1454 | 0.1334 | 0.0035 | 0.0270 | 0.2364 | 5.9203 | 473.2450* |
| −1 | −0.2057 | 0.0948 | 0.0006 | 0.0284 | −1.5427 | 10.0190 | 1,474.5070* |
| 0 | −0.2466 | 0.3793 | −0.0049 | 0.0609 | 0.2992 | 6.8546 | 635.1830* |
| 1 | −0.2107 | 0.2532 | −0.0028 | 0.0483 | 0.3095 | 4.4508 | 270.9270* |
| 2 | −0.1903 | 0.1284 | −0.0005 | 0.0358 | −0.4421 | 4.5722 | 290.9690* |
| 3 | −0.0962 | 0.1641 | 0.0049 | 0.0323 | 1.2958 | 3.7795 | 281.7610* |
| 4 | −0.0837 | 0.1780 | 0.0002 | 0.0318 | 1.4285 | 6.0385 | 598.7230* |
| 5 | −0.1406 | 0.1374 | 0.0025 | 0.0286 | 0.3016 | 5.0611 | 348.5410* |
| *Panel B. Minimal restrictions* | | | | | | | |
| −5 | −0.1500 | 0.1909 | −0.0008 | 0.0286 | 0.7080 | 10.3875 | 2,857.5290* |
| −4 | −0.1792 | 0.1037 | 0.0012 | 0.0246 | −0.7244 | 7.7912 | 1,632.8260* |
| −3 | −0.1531 | 0.2136 | 0.0032 | 0.0304 | 1.7887 | 11.7082 | 3,896.8540* |
| −2 | −0.2496 | 0.2165 | 0.0016 | 0.0313 | −0.3810 | 14.9748 | 5,845.4300* |
| −1 | −0.3381 | 0.1766 | 0.0016 | 0.0350 | −1.8121 | 20.1883 | 10,938.2100* |
| 0 | −0.5132 | 0.3793 | −0.0030 | 0.0617 | −1.1413 | 14.2590 | 5,421.7350* |
| 1 | −0.5162 | 0.2532 | −0.0058 | 0.0581 | −2.7500 | 23.1669 | 14,740.8400* |
| 2 | −0.2925 | 0.2570 | −0.0017 | 0.0397 | −1.2369 | 15.1278 | 6,109.2180* |
| 3 | −0.2187 | 0.2127 | 0.0008 | 0.0347 | 0.1087 | 9.1293 | 2,168.1820* |
| 4 | −0.2735 | 0.2483 | −0.0006 | 0.0366 | 0.3027 | 14.0193 | 5,119.5650* |
| 5 | −0.2130 | 0.2438 | 0.0007 | 0.0337 | 0.6011 | 12.8407 | 4,324.5580* |

**Notes:** The Table presents descriptive statistics for abnormal returns in the event window surrounding the EA on day 0. The abnormal returns are calculated using the market model as a benchmark for normal returns. The Table presents results for the case where the trade-to-trade return allocation procedure has been used to account for thin trading. Panel A presents results based on the use of strict trading frequency restrictions leading to a sample size of 324, while Panel B presents results when the minimal trading frequency restrictions are used leading to a sample size of 626. Jarque- Bera denotes the Jarque-Bera test for normality and *denotes that it rejects normality at a 1% significance level

| Event day | Strict restrictions Lumped | Uniform | T-to-T | Minimal restrictions Lumped | Uniform | T-to-T |
|---|---|---|---|---|---|---|
| −5 | −0.4712 | 0.2749 | −0.7014 | 0.0585 | 1.7149* | −1.8177 |
| −4 | −0.1382 | 0.2867 | −0.4624 | −0.9989 | −1.8937 | −4.1582 |
| −3 | 5.6822*** | 6.4921*** | 5.1536*** | 8.1101*** | 10.9014*** | 5.0012*** |
| −2 | 0.3983 | 0.7943 | 0.1587 | 2.0899** | 5.7505*** | 1.1563 |
| −1 | 0.6720 | 1.2299 | 0.2801 | 11.3730*** | 14.2313*** | 8.3680*** |
| 0 | 65.2899*** | 66.6416*** | 63.4647*** | 83.0658*** | 88.7635*** | 72.9626*** |
| 1 | 34.3592*** | 36.0659*** | 33.0027*** | 72.1839*** | 67.2897*** | 53.8808*** |
| 2 | 11.1761*** | 12.1343*** | 10.3733*** | 17.0236*** | 20.0431*** | 13.7488*** |
| 3 | 7.8731*** | 8.4530*** | 7.1792*** | 12.7022*** | 17.4958*** | 10.9276*** |
| 4 | 4.2409*** | 4.5904*** | 3.8790*** | 15.2631*** | 10.4261*** | 5.1189*** |
| 5 | 1.3071* | 1.6626* | 1.1295 | 6.9607*** | 9.8905*** | 4.5427*** |

**Notes:** The Table presents the test statistic $Z_{U_t}$ from (3). Columns 2 to 4 present results based on the use of strict trading frequency restrictions leading to a sample size of 324, while columns 5 to 7 present results when the minimal trading frequency restrictions are used leading to a sample size of 626. Lumped, Uniform, and T-to-T denote the lumped, uniform, and trade-to-trade return allocation procedures, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively

**Table II.**
Test of information content

they are similar across both data sets regardless of which return allocation procedure is used.

Since we have shown that the EAs contain information, it now makes sense to test whether the market's expectations of this information are realistic on average. This is done using the test statistic from (5). The average abnormal returns are depicted in Table III.

| Event day | Strict restrictions Lumped | Uniform | T-to-T | Minimal restrictions Lumped | Uniform | T-to-T |
|---|---|---|---|---|---|---|
| −5 | −0.0003 | −0.0002 | −0.0003 | −0.0009 | −0.0006 | −0.0008 |
| −4 | 0.0011 | 0.0011 | 0.0011 | 0.0014* | 0.0015* | 0.0012 |
| −3 | 0.0037** | 0.0038** | 0.0038** | 0.0031** | 0.0035** | 0.0032** |
| −2 | 0.0035*** | 0.0036*** | 0.0035*** | 0.0021*** | 0.0019*** | 0.0016*** |
| −1 | 0.0006 | 0.0006 | 0.0006 | 0.0021* | 0.0018** | 0.0016** |
| 0 | −0.0049 | −0.0048 | −0.0049 | −0.0010 | −0.0027 | −0.0030 |
| 1 | −0.0029 | −0.0028 | −0.0028 | −0.0073 | −0.0055 | −0.0058 |
| 2 | −0.0006 | −0.0005 | −0.0005 | −0.0011 | −0.0014 | −0.0017 |
| 3 | 0.0049** | 0.0049** | 0.0049** | 0.0014 | 0.0010 | 0.0008 |
| 4 | 0.0003 | 0.0003 | 0.0002 | −0.0008 | −0.0003 | −0.0006 |
| 5 | 0.0025 | 0.0026 | 0.0025 | 0.0017 | 0.0011 | 0.0007 |

**Notes:** The Table presents average abnormal returns calculated using the market model as a benchmark for normal returns. Columns 2 to 4 present results based on the use of strict trading frequency restrictions leading to a sample size of 324, while columns 5 to 7 present results when the minimal trading frequency restrictions are used leading to a sample size of 626. Lumped, Uniform, and T-to-T denote the lumped, uniform, and trade-to-trade return allocation procedures, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively, when significance is tested using test statistic $J_t$ from (5)

**Table III.**
Average abnormal returns

From the table we see that there are in fact significant positive average abnormal returns in the period surrounding the EAs. In theory this makes it possible to earn an above normal profit using mechanical trading rules, since the EA day is often known in advance from for example the financial calendar. In practice, however, since the mechanical trading rule must be used on all stocks in the sample, it is highly possible that any above normal profit will dissipate when transaction costs are taken into account. Thus, although the positive average abnormal returns are statistically significant, it is unlikely that they are economically significant given their size and the presence of transaction costs. Still when taking into account both the slow adjustment process exhibited in Table II and the significant positive average abnormal returns, our evidence indicates that there are inefficiencies in the manner with which the Danish stock market reacts to EAs.

*6.1.1 Sensitivity analyses*. We examine the robustness of these results by conducting several sensitivity analyses. First, we examine how the results vary across different trading frequency restrictions and return allocation procedures. Second, we consider how EAs with concurrent disclosures affect the results by removing them from the sample. Third, we subdivide our sample into two time periods. Finally, given the evidence of nonnormality in Table I we also perform nonparametric tests of information content.

*Trading restrictions and return allocation procedures*. We can examine the effect of using different sets of trading frequency restrictions by comparing the strict and minimal panels in Tables II and III. Such a comparison is not as straightforward as one might first assume, since we must take into consideration the behavior of the test statistic $Z_{U_t}$ from (3) when the sample size increases. Increasing the sample size from 324 to 626 causes the denominator in (3) to increase by a factor of 1.39. If we assume that the information content of the two samples is the same, then the increase in sample size will cause the numerator of (3) to increase by a factor of 1.93 $(\approx 626/324)$. Therefore under the assumption of identical information content in the two samples the increase in sample size in itself should induce an increase in the test statistic (3) of approximately 1.39.

From Table II we see that there are many days where the increase is in fact much larger. If we sum the test statistic over all event days and then compare the two data sets, we find increases of 1.75, 1.76, and 1.37 for the lumped, uniform, and trade-to-trade return allocation procedure, respectively. The evidence is therefore mixed as to whether or not the information content of EAs increases when the restrictions are relaxed. In this connection it is interesting to note that the relaxation of the trading frequency restrictions causes the average market value of equity to drop from 7.6 billion DKK to 4.2 billion DKK. This indicates that a larger proportion of small firms are now included in the sample. As mentioned, Atiase (1985) suggests that the amount of predisclosure information available to the market is less for small firms than for large firms. This would indicate that the information content of EAs for small firms should be larger than that for large firms, which is consistent with our findings using the lumped and uniform return allocation procedure. We will test this hypothesis later, and in that connection return to its validity as an explanation of the above result.

To examine the effect of different trading frequency restrictions on the average abnormal returns, we now instead turn to Table III. From this table it is evident that both panels exhibit average abnormal returns which are significantly different from

zero. The two samples, however, differ with respect to how many and which days exhibit these average abnormal returns.

While the major conclusions of information content and market inefficiency are robust across the two samples, the results do not seem entirely independent of which restrictions are placed on data with respect to trading frequency. This poses a potential problem when comparing studies that use different trading frequency restrictions. The remaining part of this study will be conducted on the data set based on the minimal restrictions, since these results concern a larger share of the market, and are therefore more general.

Contrary to the findings for trading frequency restrictions, the use of different return allocation procedures does not seem to have a noticeable effect on the results. As expected, the difference between procedures is larger under the minimal trading frequency restrictions that include the more infrequently traded stocks. Taking this into consideration, we will only present results for the trade-to-trade procedure in the remaining part of this paper. The trade-to-trade procedure is chosen since Maynes and Rumsey (1993) in their simulation studies find that it generates correct conclusions.

*Concurrent disclosures*. The results presented so far indicate that the Danish stock market is inefficient with respect to EAs. Another possible explanation for the results, however, is the previously mentioned implicit assumption that there are no other announcements in the event window. If this assumption is false then the slow reaction found above might in reality be the market reacting to the other information announced in the event window, and therefore not a sign of market inefficiency. In connection with this, the average abnormal returns might be significantly different from zero because the market is reacting to the EAs and a variety of other announcements. In fact the study by Hoskin *et al.* (1986) finds that the individual firm's abnormal returns can partially be explained by concurrent disclosures. This supports the hypothesis that the average abnormal returns we have found are in fact driven by such concurrent disclosures. We will now take a closer look at this possible explanation.

Given the date of an EA for a company, Stockwise is used to manually extract all other stock exchange announcements made by this company in the event window. These concurrent disclosures turn out to be quite common and vary greatly in subject matter. We will not attempt to evaluate, which of these announcements the market might react to, since such an evaluation would be subjective. Instead, with the exception of three instances[3] all EAs with other stock exchange announcements in the event window are deleted from the sample and the tests for information content are conducted again. Although this reduces the sample size, it serves the purpose of focusing the tests exclusively on the effect of EAs.

There are 497 other announcements in the event window. However, since a given company can have more than one announcement in the event window, these 497 announcements only pertain to 302 EAs. These EAs are deleted leaving a sample of 324 EAs. Table IV depicts all 497 concurrent disclosures by category and day of announcement. From the table we see that many types of events are evenly distributed before, on and after the EA.

The results of removing EAs with other announcements in the event window are seen in Table V. Clearly the table indicates that the EAs do have information content, demonstrating that it was not the presence of concurrent disclosures that was the sole driving factor behind the information content found above. Proceeding in the same

| Announcement | Event day −5 | −4 | −3 | −2 | −1 | 0 | 1 | 2 | 3 | 4 | 5 | All |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Annual general meeting | 2 | 2 | 3 | 1 | – | 2 | 12 | 9 | 11 | 12 | 17 | 71 |
| Acquisition/sale of share in firm | 3 | 6 | 13 | 3 | 1 | 13 | 2 | 8 | 3 | 4 | 6 | 62 |
| Notification from major shareholder | 7 | 1 | 2 | 3 | 4 | 4 | 11 | 7 | 3 | 8 | 6 | 56 |
| Management change | 1 | 2 | 1 | – | – | 10 | 9 | 3 | 2 | 4 | 1 | 33 |
| Date for EA | 14 | 4 | 4 | 5 | 1 | – | – | – | – | – | – | 28 |
| Transfer to/remove from observation list | – | – | 1 | 1 | 2 | 11 | 6 | 1 | 1 | 1 | – | 24 |
| Supplement/correction to EA | – | – | – | – | – | 6 | 6 | 5 | 2 | 2 | 1 | 22 |
| Own shares | – | – | 1 | – | – | – | 6 | 4 | – | 2 | 5 | 18 |
| Large order/contract for delivery | 1 | 1 | 3 | 2 | 1 | 2 | 1 | 1 | 1 | 2 | 2 | 17 |
| Fusion | – | – | 2 | 1 | 1 | 5 | – | 1 | 1 | 1 | 3 | 15 |
| Change in capital | – | 1 | – | 1 | 1 | 1 | 1 | 6 | – | 2 | 1 | 14 |
| Investor relations | 1 | 2 | 4 | 1 | 2 | 1 | – | 1 | – | – | – | 12 |
| Annual report | – | – | – | – | – | – | 3 | 1 | 2 | 3 | 2 | 11 |
| Statement of net asset value | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 11 |
| Strategic relations | 2 | – | – | – | 3 | 1 | 1 | 1 | – | 2 | 1 | 11 |
| Subsidiary company | – | 1 | – | – | 1 | 6 | 1 | 1 | – | – | – | 10 |
| Financial calendar | – | 4 | 1 | – | – | 1 | 1 | 1 | 1 | 1 | – | 10 |
| Extraordinary general meeting | 2 | – | 1 | 1 | – | 1 | – | – | – | 2 | 1 | 8 |
| Articles of association | 1 | 2 | – | 1 | – | 1 | – | 1 | – | – | 1 | 7 |
| Share repurchase | – | – | 1 | – | 1 | 3 | 1 | – | – | 1 | – | 7 |
| Product development | – | 1 | 2 | 1 | 1 | – | – | – | 1 | – | – | 6 |
| No quarterly reports | – | – | – | – | – | – | 2 | 1 | – | 1 | – | 4 |
| Comment on media coverage | 1 | – | – | – | – | – | 1 | 1 | – | – | 1 | 4 |
| Large investment | – | – | 1 | – | – | 2 | – | – | – | 1 | – | 4 |
| Traffic statistic/correction | – | – | – | – | 1 | 3 | – | – | – | – | – | 4 |
| Juridical decisions | – | 1 | 1 | – | – | – | – | – | – | 1 | 1 | 4 |
| Debt | 1 | 1 | – | – | – | – | – | – | 1 | – | 1 | 4 |
| Credit rating | – | – | 1 | – | – | – | – | 2 | – | – | – | 3 |
| Rationalizations | – | – | – | 1 | 1 | 1 | – | – | – | – | – | 3 |
| Request for suspension | – | – | 1 | – | – | 2 | – | – | – | – | – | 3 |
| Expectations for EA | 1 | – | 1 | 1 | – | – | – | – | – | – | – | 3 |
| Corporate governance policy | – | – | – | – | – | 2 | – | – | – | – | – | 2 |
| New business tenancies | – | 1 | – | – | – | 1 | – | – | – | – | – | 2 |
| Grant of warrants | – | – | – | – | – | – | – | – | – | 1 | – | 1 |
| Change of sector | – | – | – | 1 | – | – | – | – | – | – | – | 1 |
| Reprimand from CSE | – | – | – | – | – | – | – | 1 | – | – | – | 1 |
| Bankruptcy | 1 | – | – | – | – | – | – | – | – | – | – | 1 |
| All | 39 | 31 | 45 | 25 | 22 | 80 | 65 | 57 | 30 | 52 | 51 | 497 |

**Table IV.**
Concurrent disclosures in the event window

manner as before, it can be calculated that assuming identical information content in the sample with and without concurrent disclosures the reduction in sample size alone should reduce the test statistic $Z_{U_t}$ from (3) by a factor of 0.72. A comparison of Table V with Table II reveals that the reductions are in fact much greater. Cumulating the test statistic over all event days gives a reduction of 0.53, indicating that a proportion of the above found information content of EAs was in fact attributable to the presence of concurrent disclosures.

Comparing Table V with Table II, we see that there are now less days with a significant test statistic. The market's reaction time to EAs is in reality shorter than we

| Event day | No concurrent disclosures: Information content | No concurrent disclosures: Average abnormal returns | 1999-2001: Information content | 1999-2001: Average abnormal returns | 2002-2004: Information content | 2002-2004: Average abnormal returns |
|---|---|---|---|---|---|---|
| −5 | −2.0792 | −0.0005 | −0.2629 | −0.0009 | −2.4177 | −0.0007 |
| −4 | −2.7465 | 0.0005 | −2.4753 | 0.0007 | −3.4615 | 0.0020 |
| −3 | −2.3527 | 0.0001 | 5.1963*** | 0.0040** | 1.7123** | 0.0021 |
| −2 | 0.9343 | 0.0019 | 3.4457*** | 0.0019** | −2.0826 | 0.0014 |
| −1 | 9.4312*** | 0.0027* | 9.5460*** | 0.0016 | 1.9247** | 0.0015* |
| 0 | 40.6734*** | 0.0025** | 45.3008*** | −0.0004 | 58.6740*** | −0.0061 |
| 1 | 28.2982*** | −0.0013 | 47.2706*** | −0.0016 | 28.0697*** | −0.0110* |
| 2 | 8.3806*** | 0.0005 | 12.8634*** | −0.0002 | 6.2776*** | −0.0036 |
| 3 | 7.7825*** | −0.0008 | 9.4008*** | −0.0003 | 5.8985*** | 0.0021 |
| 4 | 2.2005** | 0.0009 | 5.8938*** | −0.0009 | 1.1173 | −0.0002 |
| 5 | −1.1092 | −0.0006 | 7.7603*** | 0.0024 | −1.8024 | −0.0013 |

**Notes:** The results are based on the use of minimal trading frequency restrictions and the trade-to-trade return allocation procedure. In addition, in columns 2 and 3 earnings announcements with concurrent disclosures in the event window are deleted, leading to a sample size of 324. Columns 4 and 5 present results for the 344 observations from the 1999-2001 period, while columns 6 and 7 present results for the 282 observations in the 2002-2004 time period. Columns labeled information content present the test statistic $Z_{U_t}$ from (3). Additionally, the Table presents average abnormal returns, whose significance is tested using test statistic $J_t$ from (5). *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively

**Table V.**
Sensitivity analyses: no concurrent disclosures and subsamples grouped by time period

were led to believe in Table II. The reaction starts on day −1 and is over by the fifth day after the announcement. This indicates that part of the slow adjustment found above can be explained by the presence of concurrent disclosures which also bring new information to the market. These conclusions, of course, rely on the assumption that there is no difference in the information content of EAs with and without concurrent disclosures. It is also still open to discussion whether a reaction time of six days is in accordance with an efficient market.

From Table V we also see that the average abnormal returns are still significantly different from zero, when EAs with concurrent disclosures are removed from the sample. Thus, it is not the presence of many other types of announcements that drives the results. It is now day −1 (at the 10 percent level) and day 0 that has average abnormal returns which are significantly positive. Thus, the removal of EAs with other announcements seems to focus the results on the market's reaction to EAs.

*Time period subsamples*. As another sensitivity analysis we subdivide our sample into two time periods, 1999-2001 and 2002-2004. This is done in order to eliminate two possible concerns. First, new Danish accounting standards went into effect in 2002, replacing the previous accounting standards effective as of 1997. One possible concern is therefore that this shift in accounting standards affects the results in some manner. Thus, we examine the time period 1999-2001, which avoids any influence from the introduction of new accounting standards, since the EAs in this period are reported under the same accounting standards and therefore congruent. A second possible concern is that our results are affected by the burst of the high-tech bubble in 2000. Our subsample from 2002-2004 avoids any possible impact from this exceptional period.

From the results presented in Table V we see that the market reaction is slow in both time periods indicating inefficiencies in the Danish stock market. In the period 1999-2001 there is still a market reaction on the fifth day after the announcement, while in 2002-2004 the market reaction is over by the fourth day after the announcement. Additionally, both time periods exhibit significant abnormal returns, although only at a 10 percent significance level in 2002-2004. Thus, although there are differences in the results across the two time periods, which is perhaps to be expected, the conclusions that can be drawn remain unchanged. We therefore conclude that the influence of shifting accounting standards and the burst of the high-tech bubble on the market reaction to EAs is limited and choose not to pursue these issues further in the following.

*Nonparametric tests*. Given the evidence of nonnormality of abnormal returns in Table I, it is possible that the inferences made with the above test statistics are invalid since the test statistics assume that the distribution of the abnormal returns approximates that of a normal distribution. We therefore also examine the information content of EAs using two nonparametric testing methodologies that do not make assumptions regarding the parametric distribution of abnormal returns. First, the rank statistic developed by Maynes and Rumsey (1993) for thinly traded stocks is applied. This statistic first ranks the standardized abnormal returns in the estimation period and event window. These ranks are then standardized and aggregated cross-sectionally for each day in the event window to produce a test statistic that has an approximately standard normal distribution. This methodology is equivalent to testing whether the market on average has had realistic expectations. We also use the methodology to test for information content by ranking the $U_{j,t}$ from (4) and then standardizing and aggregating the ranks. Finally, we perform a second test for correct average expectations using the generalized sign test from Cowan (1992).

These nonparametric tests are conducted on the data set constructed using the trade-to-trade return allocation procedure, minimal trading frequency restrictions, and exclusion of EAs with concurrent disclosures. The qualitative results of these tests are similar to those for the parametric tests presented in Table V and the test statistics will therefore not be presented here. Evidence of information content is found for days 0 through 3 and both nonparametric tests find significant positive abnormal returns on day $-1$, while the Maynes and Rumsey (1993) rank statistic also finds significant positive abnormal returns on day 0.

*6.1.2 Summary*. In summary, our results have shown that the Danish stock market reacts slowly to EAs. Additionally, Danish EAs are associated with significantly positive abnormal returns. We interpret these two results as indicating that this small stock market reacts inefficiently to EAs. The results are found to be robust, in the sense that they are not sensitive to the use of different trading frequency restrictions and return allocation procedures. Additionally, the conclusions remain unchanged regardless of how EAs with concurrent disclosures are treated, whether subsamples are examined, and whether the testing methodology is parametric or nonparametric.

### *6.2 Explaining information content*

This section shall examine the results concerning the explanation of the information content of EAs. First, the results regarding the relation between predisclosure information and information content will be presented. Then we will attempt to

uncover whether the naive or the IBES model provides the best proxy for unexpected earnings. Finally, we will conduct a multivariate analysis where abnormal returns are regressed on unexpected earnings and interaction effects between unexpected earnings and predisclosure information.

*6.2.1 Predisclosure information*. The correlations between $U_{j,t}$ from (4) and the two proxies for predisclosure information, firm size and number of analysts following a firm, are depicted in Table VI for $U_{j,t}$ cumulated over different intervals of the event window, denoted as CU.

From the Table we see that several of the correlations are significantly different from zero at a 5 percent significance level. However, the correlations are positive, indicating an opposite direction of the relationship between information content and our proxies for predisclosure information than proposed by the predisclosure information hypothesis. This is a curious result that contradicts the existing empirical evidence that accepts this hypothesis. These prior studies have been conducted on data from the US (e.g. Atiase, 1985 and Dempsey, 1989) and the UK (e.g. Rippington and Taffler, 1995 and Pope and Inyangete, 1992) and therefore the hypothesis has previously only been tested in large stock markets. Our result seems to indicate that the conclusions of these studies do not pertain to small stock markets, since we find opposing results.

Faced with this interesting result, one possibility is simply that firm size and number of analysts following a firm provide poor proxies for the amount of

| | | PPM | | | SRO | |
|---|---|---|---|---|---|---|
| | | MV | Log(MV) | NA | MV | NA |
| *Panel A. With concurrent disclosures* ($n = 626$) | | | | | | |
| CU[0;0] | estimate | 0.1148 | 0.1260 | 0.1310 | 0.2039 | 0.2368 |
| | prob > \|r\| | 0.0040 | 0.0016 | 0.0010 | <0.0001 | <0.0001 |
| CU[0;1] | estimate | 0.0682 | 0.0844 | 0.0933 | 0.2081 | 0.2456 |
| | prob > \|r\| | 0.0881 | 0.0348 | 0.0195 | <0.0001 | <0.0001 |
| CU[−5;5] | estimate | 0.0392 | 0.0595 | 0.0611 | 0.1725 | 0.1953 |
| | prob > \|r\| | 0.3272 | 0.1370 | 0.1269 | <.0001 | <.0001 |
| CU[0;5] | estimate | 0.0438 | 0.0571 | 0.0700 | 0.1659 | 0.2062 |
| | prob > \|r\| | 0.2739 | 0.1535 | 0.0803 | <0.0001 | <0.0001 |
| *Panel B. Without concurrent disclosures* ($n = 324$) | | | | | | |
| CU[0;0] | estimate | 0.0306 | 0.1254 | 0.1130 | 0.2697 | 0.2957 |
| | prob > \|r\| | 0.5832 | 0.0239 | 0.0421 | <0.0001 | <0.0001 |
| CU[0;1] | estimate | 0.0207 | 0.1341 | 0.1183 | 0.2503 | 0.2771 |
| | prob > \|r\| | 0.7103 | 0.0157 | 0.0333 | <0.0001 | <0.0001 |
| CU[−5;5] | estimate | 0.0067 | 0.0970 | 0.0925 | 0.2313 | 0.2712 |
| | prob > \|r\| | 0.9044 | 0.0814 | 0.0964 | <0.0001 | <.0001 |
| CU[0;5] | estimate | 0.0085 | 0.1159 | 0.1104 | 0.2347 | 0.3071 |
| | prob > \|r\| | 0.8790 | 0.0370 | 0.0472 | <0.0001 | <0.0001 |

**Notes:** Based on data with minimal trading frequency restrictions and use of the trade-to-trade return allocation procedure. CU denotes cumulated information content, where information content is measured using $U_{j,t}$ from (4). The cumulation period relative to the EA day is given in brackets. Columns 3 to 5 present Pearson-Product Moment (PPM) correlation coefficients, while columns 6-7 present Spearman Rank Order (SRO) correlation coefficients. MV denotes market value of equity measured the day before the beginning of the event window. Log(MV) denotes the natural logarithm of this value. NA denotes the number of analysts following a firm as reported by IBES

**Table VI.**
Correlations between predisclosure information and information content

predisclosure information available for a firm. For this reason we will examine the relationship between information content and predisclosure information using liquidity as a third proxy for the amount of predisclosure information. Shores (1990) also used liquidity as a proxy for predisclosure information arguing that trading by informed investors is more visible for thinly traded stocks thereby reducing the potential gain to private information. This reduces incentives for private information gathering and dissemination leading to a negative relationship between thinness and predisclosure information. Since liquidity is expected to be negatively related to thinness, we expect a negative relationship between liquidity and information content. Lacking a theoretically "best" definition of liquidity, we will measure liquidity using turnover, TO, defined as the number of shares traded in the 30 trading days before the event window divided by the total number of outstanding shares. This measure is chosen since, unlike measures such as dollar value of trades, it adjusts for firm size, and is therefore not by definition highly correlated with firm size. We will not report the results here, but simply note that we again find an opposite relationship to that predicted by theory, since the correlation between our measure of liquidity and information content is positive. Although this relationship is not as strong as when predisclosure information is proxied by firm size and analyst following, it underscores the curious result of a positive relationship between information content and proxies for predisclosure information.

Given that we could not measure predisclosure information directly, but instead used different variables as proxies, there are two possible interpretations of the above results. First, if the variables chosen provide good proxies for predisclosure information, as research in the US and UK has indicated, then the Danish stock market reacts more to EAs from firms that have a larger level of predisclosure information. This interpretation is in clear contradiction with the predisclosure information hypothesis. A second interpretation is simply that these variables for some reason provide poor proxies for predisclosure information in the Danish stock market. In connection with this interpretation, it is plausible that the quality of the EA announcement is higher for large firms followed by many analysts, therefore resulting in a larger market reaction to EAs from these firms. In particular this high quality effect could be more pronounced for the non-quantitative component of the EA. Additionally, it is possible that the market is simply less interested in small firms, and therefore in essence underreacts to the information content of small EAs. Thus, it is possible that there are two factors working in opposite directions that affect information content. One being the amount of predisclosure information, which has a negative impact on information content, and another positive effect from, for example, a higher quality EA. An explanation for the Danish results that is consistent with all of the previous empirical work is then simply, that the level of predisclosure information in Denmark is so low that the positive effect dominates.

Since the latter explanation is consistent with theory and former empirical work it seems most plausible. Additionally, this explanation is interesting in light of the results of Plenborg (1998). He found a higher association between stock returns and unexpected earnings in Denmark compared to the US. He attributed this to the more flexible accounting standards of Denmark compared to the US, and concluded that his findings contradicted the idea of the then current FASB agenda which emphasized the comprehensive income statement. However, as mentioned in the introduction, some of

his sensitivity analyses seem to indicate that his finding of a higher degree of association is due to a lower level of predisclosure information in the Danish than the US market. Indeed, our results seem to support this interpretation. In light of this new evidence it therefore seems premature to draw any conclusions regarding preferred accounting standards based on Danish evidence. Instead, it seems that the results from the small Danish stock market should be interpreted as indicating the importance of the surrounding information environment rather than being caused by different accounting standards.

Our above finding of a positive relationship between information content and firm size necessitates a reexamination of our earlier indications of an increased information content when trading frequency restrictions are relaxed. Previously, we proposed the firm size-related differential information hypothesis as a possible explanation of this result, since the relaxation of the trading frequency restrictions led to an increased proportion of small firms in the sample. However, as we are unable to accept this hypothesis, the result must be due to other factors. Another possibility is the presence of concurrent disclosures. We saw in the section on concurrent disclosures that these were associated with an information content. If these disclosures are more common for small than large firms, this would lead to the increased information content found. An examination of the disclosures reveals that this is not the case. Indeed, 58 percent of the deleted EAs with concurrent disclosures are in the sample with strict trading frequency restrictions, so the increase in information content when trading frequency restrictions are relaxed does not stem from a greater presence of concurrent disclosures. However, it does seem that the information content of the EAs with concurrent disclosures in the sample with strict trading frequency restrictions is smaller than that for those added when the trading frequency restrictions are relaxed. Thus, the average of the sum of $U_{j,t}$ from (4) across the event window in the sample with strict trading frequency restrictions is 21 for EAs with concurrent disclosures, but 27 for those that are added when the trading frequency restrictions are relaxed. Contrary to this, for EAs without concurrent disclosures the average of the sum of $U_{j,t}$ from (4) across the event window in the sample with strict trading frequency restrictions is 20, but only 16 for those that are added when the trading frequency restrictions are relaxed. Thus, it seems that it is the concurrent disclosures that are driving the increase in information content of EAs when trading frequency restrictions are relaxed and not firm size. This supports our above finding of a positive relationship between information content and firm size. In addition, it underscores the possible impact of including EAs with concurrent disclosures in the sample.

*6.2.2 Unexpected earnings*. Tables VII and VIII present correlations between abnormal returns and unexpected earnings from the naive model and the IBES model, respectively. Since several of the variables needed to calculate unexpected earnings from the two models have missing observations, the correlations differ with respect to how many observations, $N$, they are based on. If we evaluate the performance of the two models by the number of correlations that are significantly different from zero at a 5 percent significance level, we see that the IBES model performs better than the naive model using both PPM and SRO correlation coefficients. This is in line with previous research and supports the notion that financial analyst forecasts are superior proxies for the market's expectations. While there are many proposed sources of this superiority, Brown *et al.* (1987b) find that they can attribute part of the superiority of

| | | I/B/E/S | | | Account data | | |
|---|---|---|---|---|---|---|---|
| | | None | \|E[eps]\| | MV | None | \|E[eps]\| | MV |
| *Panel A. PPM correlation coefficient* | | | | | | | |
| | estimate | −0.0295 | 0.0563 | 0.0816 | 0.0115 | 0.0403 | 0.0099 |
| CAR[0;1] | prob > \|r\| | 0.5336 | 0.2342 | 0.0883 | 0.7780 | 0.3230 | 0.8093 |
| | *n* | 449 | 449 | 437 | 605 | 605 | 592 |
| | estimate | −0.0063 | −0.0050 | 0.0971 | 0.0187 | −0.0316 | 0.0546 |
| CAR[−5;5] | prob > \|r\| | 0.8941 | 0.9157 | 0.0425 | 0.6468 | 0.4376 | 0.1848 |
| | *n* | 449 | 449 | 437 | 605 | 605 | 592 |
| | estimate | −0.0175 | 0.0023 | 0.0616 | 0.0096 | −0.0476 | 0.0350 |
| CAR[0;5] | prob > \|r\| | 0.7123 | 0.9611 | 0.1985 | 0.8133 | 0.2420 | 0.3955 |
| | *n* | 449 | 449 | 437 | 605 | 605 | 592 |
| *Panel B. SRO correlation coefficient* | | | | | | | |
| | estimate | 0.0328 | 0.0852 | 0.0568 | 0.0354 | 0.0820 | 0.0514 |
| CAR[0;1] | prob > \|r\| | 0.4883 | 0.0713 | 0.2363 | 0.3847 | 0.0439 | 0.2115 |
| | *n* | 449 | 449 | 437 | 605 | 605 | 592 |
| | estimate | 0.0418 | 0.0483 | 0.0564 | 0.0678 | 0.0942 | 0.0860 |
| CAR[−5;5] | prob > \|r\| | 0.3771 | 0.3067 | 0.2398 | 0.0959 | 0.0204 | 0.0364 |
| | *n* | 449 | 449 | 437 | 605 | 605 | 592 |
| | estimate | 0.0531 | 0.0747 | 0.0675 | 0.0696 | 0.0771 | 0.0845 |
| CAR[0;5] | prob > \|r\| | 0.2614 | 0.1138 | 0.1588 | 0.0870 | 0.0580 | 0.0399 |
| | *n* | 449 | 449 | 437 | 605 | 605 | 592 |

**Notes:** Based on the data set with minimal trading frequency restrictions. In addition the trade-to-trade return allocation procedure is used. CAR denotes cumulated abnormal returns, where the event window interval of cumulation is given in brackets. Columns 3-5 are based on actual eps from the I/B/E/S database, while colums 6-8 use actual eps from Account data. None denotes no use of a deflator in the calculation of unexpected earnings. |E[eps]| and MV denote the deflator's absolute value of forecast and market value, respectively

**Table VII.**
Correlation between naïve model unexpected earnings and CARs

financial analysts' forecasts to their timing advantage, in that they are able to utilize the information that the market receives between two EAs in their forecasts. We therefore conclude that the IBES model provides a better proxy for unexpected earnings in Denmark than the naive model.

From Table VIII it does not seem that the performance of the IBES model is dependent on the source of actual eps. In particular, it is not clear that it performs worse when actual eps are drawn from the I/B/E/S database. This is not in accordance with the aforementioned findings of Philbrick and Ricks (1991). Given this finding, we find it most reasonable to use actual eps from the I/B/E/S database, where the forecasts are also from. It is also of interest to examine the impact of using different deflators on the performance of the model. Again Table VIII clearly indicates that using the market value of equity at the beginning of the period as the deflator leads to the most robust performance of the IBES model, which is consistent with the theoretical findings of Christie (1987). Thus, we can conclude that of the models, which we have examined, the IBES model based on actual earnings data from the I/B/E/S database and using market value of equity at the beginning of the period as the deflator provides the best proxy for unexpected earnings.

*Sensitivity analyses*. To check the robustness of this conclusion, we first note that the tables in this section have shown that the number of observations underlying the

| | | I/B/E/S | | | Account data | | |
|---|---|---|---|---|---|---|---|
| | | None | \|E[eps]\| | MV | None | \|E[eps]\| | MV |
| *Panel A. PPM correlation coefficient* | | | | | | | |
| | estimate | 0.0400 | 0.0354 | 0.1801 | 0.0367 | 0.0562 | 0.1734 |
| CAR[0;1] | prob > \|r\| | 0.4011 | 0.4568 | 0.0002 | 0.4359 | 0.2317 | 0.0002 |
| | *n* | 444 | 444 | 432 | 454 | 454 | 442 |
| | estimate | 0.0329 | 0.0494 | 0.2284 | −0.0010 | 0.0633 | 0.1761 |
| CAR[−5;5] | prob > \|r\| | 0.4888 | 0.2995 | <.0001 | 0.9825 | 0.1782 | 0.0002 |
| | *n* | 444 | 444 | 432 | 454 | 454 | 442 |
| | estimate | 0.0244 | −0.0005 | 0.1700 | −0.0042 | 0.0228 | 0.1362 |
| CAR[0;5] | prob > \|r\| | 0.6083 | 0.9925 | 0.0004 | 0.9290 | 0.6284 | 0.0041 |
| | *n* | 444 | 444 | 432 | 454 | 454 | 442 |
| *Panel B. SRO correlation coefficient* | | | | | | | |
| | estimate | 0.1036 | 0.1148 | 0.1308 | 0.1171 | 0.1192 | 0.1456 |
| CAR[0;1] | prob > \|r\| | 0.0291 | 0.0155 | 0.0065 | 0.0125 | 0.0110 | 0.0021 |
| | *n* | 444 | 444 | 432 | 454 | 454 | 442 |
| | estimate | 0.0686 | 0.0647 | 0.0835 | 0.0914 | 0.0925 | 0.1247 |
| CAR[−5;5] | prob > \|r\| | 0.1489 | 0.1737 | 0.0832 | 0.0517 | 0.0489 | 0.0087 |
| | *n* | 444 | 444 | 432 | 454 | 454 | 442 |
| | estimate | 0.0766 | 0.0786 | 0.0890 | 0.0767 | 0.0876 | 0.1110 |
| CAR[0;5] | prob > \|r\| | 0.1070 | 0.0981 | 0.0647 | 0.1028 | 0.0623 | 0.0196 |
| | *n* | 444 | 444 | 432 | 454 | 454 | 442 |

**Notes:** Based on the data set with minimal trading frequency restrictions. In addition the trade-to-trade return allocation procedure is used. CAR denotes cumulated abnormal returns, where the event window interval of cumulation is given in brackets. Columns 3-5 are based on actual eps from the I/B/E/S database, while colums 6-8 use actual eps from Account data. None denotes no use of a deflator in the calculation of unexpected earnings. |E[eps]| and MV denote the deflator's absolute value of forecast and market value, respectively

**Table VIII.**
Correlation between IBES model unexpected earnings and CARs

correlations differ across the two models and sources of actual eps. One could question whether this affects the results in some way. We therefore calculate correlations for a data set, where all observations with a missing value for any of the variables involved in calculating unexpected earnings are deleted leaving 421 observations. The results are consistent with the above conclusions and hence will not be depicted.

Additionally, correlations are calculated for a data set that only contains EAs without concurrent disclosures. Although the untabulated results support our conclusion of the superiority of the IBES model, both models perform poorly. This is somewhat surprising given that we have found evidence indicating that the concurrent disclosures also have information content. Thus, we would have expected that removing EAs with concurrent disclosures enhanced the relationship between unexpected earnings and abnormal returns. We interpret our finding of the opposite as a result of the reduced sample size.

Our conclusion of the superiority of the IBES model over the naive model therefore seems robust towards these two alterations. In the next section we will test whether the two models have explanatory power over each other by including them in a multivariate analysis.

*6.2.3 Multivariate analysis*. In addition to examining the performance of the different proxies for unexpected earnings separately, it is also of interest to see if they

have explanatory power over each other and therefore capture different information. Previous studies by Hughes and Ricks (1987) and Brown *et al.* (1987a) have found that this is in fact the case. To examine this, we will conduct a multivariate regression, where CARs are regressed on proxies of unexpected earnings from both the IBES and naive model. From the above analysis it is clear that there are many combination possibilities with respect to choice of deflator and source of actual earnings data. We will not present all the possibilities here, but instead concentrate on the choices that led to the best performance of each model individually. Our unexpected earnings measure for the naive and IBES model is therefore based on actual earnings data from the I/B/E/S database and uses market value as the deflator. We will also examine if there is asymmetry in the market response to EAs by including a dummy variable for negative unexpected earnings and the interaction between this dummy variable and unexpected earnings in the regression. Additionally, we follow Christensen *et al.* (2004) and examine whether the market reaction to a given level of earnings surprise is lower for firms with a higher level of predisclosure information by regressing CARs on unexpected earnings and interaction effects between unexpected earnings and proxies for predisclosure information. Finally, in all regressions we control for industry and time effects by including dummy variables.

Table IX presents results where abnormal returns cumulated over the announcement day and the day after are regressed on different earnings measures[4]. From regressions (1) and (2), we see that both the IBES and naive models of unexpected earnings are significant when included separately. Additionally, the coefficients are positive as expected. However, while the naive model is only significant at the 10 percent level, the IBES model is significant at the 1 percent level. The regression of CARs on the IBES model has an $R^2$ that is almost twice as large as that of the regression of CARs on the naive model. Supporting these indications of the IBES model's superiority, we find in regression (3) that only the IBES model is significant when both earnings surprise models are included in a regression simultaneously. Thus, there is no evidence that the two proxies for unexpected earnings have explanatory power over each other. This result is in conflict with that of Hughes and Ricks (1987) and Brown *et al.* (1987a) and indicates that in Denmark the naïve model does not contain any information not included in the IBES model of unexpected earnings. Finally, although the adjusted $R^2$s are low, indicating that a large part of the abnormal returns are still left unexplained, they are comparable to similar studies (see Lev (1989) for a review).

In regressions (4) and (5) we have included a dummy variable for negative unexpected earnings and its interaction with the unexpected earnings measure in order to test for an asymmetry in the market reaction to EAs. Indeed, the results indicate that an asymmetry is present, since it is only the coefficient of the interaction between the dummy variable for negative unexpected earnings and IBES UEs that is significantly positive. Thus, there is a negative market reaction to negative unexpected earnings, but no market reaction to positive unexpected earnings. Although this result is perhaps a bit surprising, it is similar to the findings of Kothari *et al.* (2005) for voluntary management earnings forecasts. As in their study, we interpret our results as indicating that managers accumulate and withhold bad news but leak good news. Thus, while the negative unexpected earnings is a surprise to investors this is not the case for the positive unexpected earnings.

| Independent variable | Regression (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Intercept | 0.0150 | 0.0203* | 0.0209* | 0.0178 | 0.0237* |
| | (0.0117) | (0.0114) | (0.0114) | (0.0129) | (0.0124) |
| Naïve UE | 0.1070* | | 0.0077 | 0.0650 | |
| | (0.0584) | | (0.0671) | (0.0708) | |
| IBES UE | | 0.3585*** | 0.3553*** | | 0.1049 |
| | | (0.1012) | (0.1172) | | (0.1574) |
| Neg. naïve | | | | 0.0000 | |
| | | | | (0.0103) | |
| Neg. naïve*Naive UE | | | | 0.1888 | |
| | | | | (0.1625) | |
| Neg. IBES | | | | | − 0.0003 |
| | | | | | (0.0098) |
| Neg. IBES*IBES UE | | | | | 0.4694** |
| | | | | | (0.2167) |
| *Industry* | | | | | |
| Energy | − 0.0011 | − 0.0040 | − 0.0051 | − 0.0031 | − 0.0055 |
| | (0.0393) | (0.0383) | (0.0383) | (0.0394) | (0.0383) |
| Materials | − 0.0048 | − 0.0057 | − 0.0069 | − 0.0063 | − 0.0073 |
| | (0.0177) | (0.0173) | (0.0173) | (0.0178) | (0.0173) |
| Consumer discretionary | − 0.0094 | − 0.0053 | − 0.0055 | − 0.0098 | − 0.0068 |
| | (0.0155) | (0.0157) | (0.0158) | (0.0155) | (0.0157) |
| Consumer staples | 0.0018 | 0.0041 | 0.0030 | 0.0011 | 0.0059 |
| | (0.0161) | (0.0159) | (0.0158) | (0.0161) | (0.0159) |
| Health care | − 0.0091 | − 0.0100 | − 0.0112 | − 0.0119 | − 0.0137 |
| | (0.0142) | (0.0138) | (0.0139) | (0.0145) | (0.0139) |
| Financials | 0.0181 | 0.0174 | 0.0163 | 0.0162 | 0.0156 |
| | (0.0229) | (0.0223) | (0.0223) | (0.0230) | (0.0223) |
| Information technology | − 0.0636*** | − 0.0590*** | − 0.0602*** | − 0.0633*** | − 0.0579*** |
| | (0.0168) | (0.0164) | (0.0163) | (0.0168) | (0.0164) |
| Telecom services | − 0.0451 | − 0.0465 | − 0.0476 | − 0.0483 | − 0.0507 |
| | (0.0393) | (0.0383) | (0.0383) | (0.0395) | (0.0383) |
| Utilities | − 0.0331 | − 0.0346 | − 0.0349 | − 0.0351 | − 0.0377 |
| | (0.0955) | (0.0931) | (0.0929) | (0.0957) | (0.0929) |
| Time dummies | Yes | Yes | Yes | Yes | Yes |
| *n* | 437 | 432 | 430 | 437 | 432 |
| Adj. $R^2$ | 0.0244 | 0.0504 | 0.0494 | 0.023 | 0.0566 |

**Notes:** Coefficients with standard errors given in parentheses from regression analyses of the market reaction to EAs. Results are based on the data set with minimal trading frequency restrictions and use of the trade-to-trade return allocation procedure. The dependent variables are the abnormal returns cumulated over the announcement day and the day after. Naïve UE is the difference between this year's and last year's eps from the I/B/E/S database deflated by the market value of equity. IBES UE is the difference between this year's eps and consensus analyst forecast eps from the I/B/E/S database deflated by the market value of equity. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively

**Table IX.**
Regressions of CARs on unexpected earnings

Table X presents results from regressing abnormal returns cumulated over the announcement day and the day after on unexpected earnings and interactions effects between unexpected earnings and proxies for predisclosure information. Since we found above that the IBES model not only performs better than the naive model, but also contains all information in the latter, we only present results based on the IBES model of unexpected earnings. In regression (1) predisclosure information is proxied using the market value of equity, and the resulting interaction effect is in fact significantly negative. Regression (2) proxies predisclosure information using the number of analysts following a firm, but finds an insignificant interaction effect. Although not presented here, the results are slightly different when abnormal returns are cumulated over the entire event window or from event day 0 to 5. When this is the case the interaction effect obtained when predisclosure information is proxied using the number of analysts following a firm, is significantly negative. However, when both interaction effects are included together they are both insignificant, and the results of testing this model down, by removing the most insignificant variables first, leaves only the interaction effect obtained using the market value of equity. Thus, we conclude that the strongest results are found when predisclosure information is proxied using the market value of equity.

These results indicate that the market reacts less to a given level of earnings surprise from firms with more predisclosure information. This result is in line with

| | (1) | | (2) | |
|---|---|---|---|---|
| Independent variable | Coefficient | Std. error | Coefficient | Std. error |
| Intercept | 0.0221* | (0.0114) | 0.0205* | (0.0114) |
| IBES UE | 0.5518*** | (0.1291) | 0.5412*** | (0.1611) |
| MV*IBES UE | −0.3632** | (0.1519) | | |
| NA*IBES UE | | | −0.0906 | (0.0622) |
| *Industry* | | | | |
| Energy | −0.0016 | (0.0381) | −0.0045 | (0.0383) |
| Materials | −0.0077 | (0.0172) | −0.0061 | (0.0173) |
| Consumer discretionary | −0.0071 | (0.0156) | −0.0056 | (0.0156) |
| Consumer staples | 0.0030 | (0.0158) | 0.0038 | (0.0158) |
| Health care | −0.0119 | (0.0138) | −0.0110 | (0.0138) |
| Financials | 0.0163 | (0.0222) | 0.0154 | (0.0223) |
| Information technology | −0.0583*** | (0.0163) | −0.0597*** | (0.0163) |
| Telecom services | −0.0477 | (0.0381) | −0.0472 | (0.0383) |
| Utilities | −0.0365 | (0.0926) | −0.0343 | (0.0930) |
| Time dummies | Yes | | Yes | |
| *n* | 432 | | 432 | |
| Adj. $R^2$ | 0.0611 | | 0.0530 | |

**Notes:** Based on the data set with minimal trading frequency restrictions and use of the trade-to-trade return allocation procedure. The dependent variables are the abnormal returns cumulated over the announcement day and the day after. IBES UE is the difference between this year's eps and consensus analyst forecast eps from the I/B/E/S database deflated by the market value of equity. MV*IBES UE and NA*IBES UE are the IBES UE multiplied by the market value of equity the day before the event window (MV) and the number of analysts following a firm (NA), respectively. *, **, and ***denote statistical significance at the 10%, 5%, and 1% level, respectively

**Table X.**
Regressions of CARs on unexpected earnings and predisclosure information

previous literature, i.e. Kross and Schroeder (1988) and Christensen *et al.* (2004). Although at first glance this result might seem to conflict with our earlier finding of a positive correlation between information content and proxies for predisclosure information, this is not necessarily the case. As mentioned in the section reviewing previous literature, the correlations capture the joint effect of the amount of surprise in an EA and the magnitude of the reaction to a given level of surprise. The results presented here only capture the latter effect. Thus, an interpretation that is consistent with both of our results is that although the Danish market reacts less to a given level of earnings surprise in EA announcements from large firms presumed to have more predisclosure information, there is a higher amount of surprise in these EAs from large firms. As mentioned, this higher level of surprise could be caused by a higher quality of EAs from large firms, for example in their non-quantitative components. Therefore, in conclusion we find evidence supporting the predisclosure hypothesis, since the market reacts less to a given level of earnings surprise from firms presumed to have a high level of predisclosure information. At the same time, our evidence indicates that the level of predisclosure information in Denmark is low enough that the positive effect from for example higher quality EAs dominates, such that the overall effect is higher information content in EAs from large firms.

## 7. Conclusion

This paper contributes to the existing literature by analyzing the information content of EAs in a small stock market with accounting standards similar to those of the often studied larger US and UK stock markets. As in the larger stock markets, we find that Danish EAs have information content, indicating that they bring relevant new information to the Danish stock market. However, our evidence indicates that the information environment of this small stock market is such that the market is slow to incorporate new information from the EAs into stock prices. Adding to this evidence of inefficiency we also find significant positive average abnormal returns, indicating that the market's average expectations of the EAs are unrealistic. These findings are found to be robust with regards to variations in trading frequency restrictions, return allocation procedures, treatment of concurrent disclosures, time subsamples, and nonparametric tests.

While our results indicate an inefficiency in the Danish stock market and therefore contradict the general finding of efficiency with respect to EAs in large stock markets, it is interesting to note that other studies have found similar results. Pellicer and Rees (1999) also find a reaction time of six days in the Spanish stock market, and studies by for example Ball and Kothari (1991), Elsharkawy and Garrod (1996), and Pellicer and Rees (1999) have also found significant positive abnormal returns in the US, the UK, and Spain respectively. These results are puzzling, and it still remains an open question why some stock markets are found to react inefficiently to the annual announcement of earnings.

We find a positive correlation between proxies for predisclosure information and the information content of EAs. This result not only contradicts our ex ante expectations regarding the direction of the relationship, but also the findings of previous studies. However, in line with previous studies we find a smaller market reaction to a given level of earnings surprise from firms with more predisclosure information, which supports the predisclosure information hypothesis. Thus, our two results combined

seem to suggest that although the market reacts less to a given level of earnings surprise in EAs from large firms presumed to have more predisclosure information, there is a higher amount of surprise in EAs from large firms. We believe that the latter is due to a low level of predisclosure information in Denmark, which causes the positive effect from, for example, higher quality EAs for large firms to dominate the negative effect from large firms having more predisclosure information. This is interesting given the findings in Plenborg (1998) of a higher degree of association between stock returns and unexpected earnings in Denmark compared to the US. Our results therefore contribute to the existing literature by indicating that this higher degree of association is not caused by superior Danish accounting standards as suggested by Plenborg (1998), but instead is simply due to a lower level of predisclosure information.

Finally, we find that using consensus analyst forecasts as proxies for the market's expectations of earnings provides a better model for unexpected earnings than a naive model that assumes earnings follow a random walk. Our results therefore support the general assumption that models based on analysts' forecasts provide the best proxies for unexpected earnings, while contradicting the findings of Hughes and Ricks (1987) and O'Brien (1988). Additionally, we find an asymmetry in the market reaction, in that there is a negative market reaction to negative unexpected earnings, but no reaction to positive unexpected earnings. This supports the findings of Kothari *et al.* (2005) and suggests that managers accumulate and withhold bad news but leak good news.

**Notes**

1. During our period of interest, 1 EUR was approximately equal to 7.5 DKK.
2. The author gratefully acknowledges the contribution of Thomson Financial for providing earnings per share forecast data, available through the Institutional Brokers Estimate System. This data has been provided as part of a broad academic program to encourage earnings expectations research.
3. In the interest of keeping our sample as large and general as possible, we make three exceptions to our rule of deleting all EAs with concurrent announcements. First, since we use daily returns an EA is not deleted if a supplement/correction to the EA is announced on the same day. Second, if the annual general meeting, annual report, or financial calendar is announced on the same day then the EA is not deleted. Since the EA itself often contains this information, it does not seem reasonable to delete EAs simply because this information is also publicized in a separate announcement. Third, from October 1, 2002 firms are required to disclose insider transactions, where insiders are defined as people with access to private information, when the market value exceeds 50,000 DKK on a given trading day. Since these disclosures are very frequent and naturally tend to follow EAs in connection with stock option plans etc., we choose not to delete EAs with concurrent announcements of this type. Finally, these exceptions do not affect the conclusions drawn from our results. Indeed, if these EAs are also deleted, thereby reducing the sample to 274 EAs, the market reaction still persists until the 4th day after the EA with signi.cant positive abnormal returns.
4. The results are similar and lead to the same conclusions when abnormal returns are cumulated over event day $-5$ to 5 or event day 0 to 5.

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