
THE INFORMATION CONTENT OF EARNINGS ANNOUNCEMENTS IN DENMARK

Carina Sponholtz
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Carina Sponholtz
University of Aarhus

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1Address correspondence: Carina Sponholtz, Department of Management, Building 322, University of Aarhus, DK-8000 Aarhus C, Denmark. E-mail: csponholtz@econ.au.dk. The author is grateful for helpful comments from Jan Bartholdy, Ken L. Bechmann, Bent Jesper Christensen, Kasper Hansen, Johannes Raaballe, and workshop participants at the European Accounting Association conference (EAA, Prague, April 2004) and the University of Aarhus.
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Abstract

This paper uses the traditional event study method to examine the information content of annual earnings announcements in the small Danish stock market. Using data from 1999-2001 we find abnormal volatility in the days surrounding the announcements, indicating that they do 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, we find significant positive abnormal returns accompanying the announcements. These results are shown to be robust across various methodologies. Surprisingly, we find a positive relationship between the information content of earnings announcements and proxies for predisclosure information. This contradicts previous studies, and we interpret it as evidence of a low level of pre-announcement information. Additionally, this result supports the notion that prior evidence of a higher degree of association between stock returns and unexpected earnings in Denmark compared to the US is due to less pre-announcement information and not superior Danish accounting standards as previously suggested. Confirming the results of similar studies, we find that unexpected earnings are best proxied using a model based on consensus analyst forecasts.

Keywords: earnings announcements, event study, efficiency, firm size, predisclosure information, thin trading
1 Introduction

One of the most compelling and intriguing research questions of our time is how information is reflected in the price of stocks. The notion of stock market efficiency, first introduced by Fama (1965), has played a central role in both theoretical and empirical work on the topic. 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 modelling 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.

While the efficiency hypothesis avoids the issue of how individuals process information and implicitly assumes homogeneous information, the disclosure lit-
erature has provided additional insight by more explicitly modelling 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. These theoretical and empirical studies therefore indicate that the information environment plays a central role in the stock market’s reaction to information disclosures.

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 an earnings announcement (EA) 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, Jones, Leftwich and Zmijewski (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, Møller and Thinggaard (2000) conducted a study using daily data. As argued, however, it seems that results of such studies of different markets with different information environments should be of interest to a much broader audience.

In this paper, we analyze Danish 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 similar to those of the often studied larger US and UK
stock markets. The manner in which small stock markets react to earnings announcements is interesting 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 International Accounting Standards (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 highly 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 be 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 relationship between the information content of EAs and proxies for predisclosure information. Given previous findings 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 provides a brief description of the Danish stock market. Following this we introduce the methodology used in this study. The fourth section describes our data. In the fifth section we present the results. Our conclusion is given in the sixth section.

2 The Danish stock market

The Copenhagen Stock Exchange (CSE) constitutes the Danish stock market. During our period of interest, 1999 - 2001, the market capitalization of listed companies rose from 629.3 billion DKK\textsuperscript{1} ultimo 1998 to 896.1 billion DKK ultimo 2000, to fall to a level of 737.9 billion DKK ultimo 2001. However, 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 approximately 70\% of this value. The total turnover of listed companies rose from 432.9 billion DKK in 1999 to 757.5 billion DKK in 2000 to fall to 550.5 billion DKK in 2001. Again, however, the KFX-index accounts for a large share of this, approximately 80\% in 2000 and 2001, 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 our period of interest.

3 Methodology

The methodology used in this study is the standard event study methodology, see for example Campbell, Lo and MacKinlay (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

\[ R_{j,t} = \alpha_j + \beta_j R_{m,t} + \varepsilon_{j,t} \]  

(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

\[
\hat{\sigma}^2_j = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_{j,t}^2}{T - 2}
\]

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 \( AR \)s can be calculated from

\[
\hat{V}_j = I \hat{\sigma}^2_j + X_j^* \left( X_j X_j \right) X_j^* \hat{\sigma}^2_j
\]

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.

### 3.1 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: 16)). 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, Philbrick and Stephan (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

\[ R_{j,n_t} = \alpha_j n_t + \beta_j R_{m,n_t} + \sum_{s=0}^{n_t-1} \xi_{j,t-s} \]

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 \( n_t \sigma_j^2 \), 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

\[ \hat{\epsilon}_{j,n_t} = R_{j,n_t} - \hat{\alpha}_j n_t - \hat{\beta}_j R_{m,n_t} \]

while the variance of the abnormal returns \( \hat{\sigma}_j^2 \) is calculated from

\[ \hat{\sigma}_j^2 = \frac{\sum_{t=1}^{T_j} (\hat{\epsilon}_{j,n_t}/\sqrt{n_t})^2}{T_j - 2} \]

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
ARs 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.

### 3.2 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 first subsection, while the next deals with the last question.

#### 3.2.1 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 \( \hat{\mathcal{V}} \) from (2) using the following test statistic from Patell (1976)

\[
Z_{U_t} = \frac{\sum_{j=1}^{N} (U_{j,t} - 1)}{\sqrt{\sum_{j=1}^{N} \frac{2(T_j - 3)}{T_j - 6}}} \sim N(0,1) \tag{3}
\]
where
\[ U_{j,t} = \frac{AR_{j,t}^2}{\hat{V}_{j,t}} \cdot \frac{T_j - 4}{T_j - 2} \] (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.

### 3.2.2 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, Musumeci and Poulsen (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

$$J_t = \frac{1}{N} \sum_{j=1}^{N} SAR_{j,t} \sim N(0, 1)$$

(5)

where $SAR_{j,t} = \frac{AR_{j,t}}{\sqrt{V_{j,t}}}$ and $\sqrt{V_{j,t}}$ 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.

3.3 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 predislosure information to firm characteristics. EAs from firms with a high level of predislosure 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.

3.3.1 Predisclosure information

As mentioned in the introduction, theoretical work has indicated that the information environment has an impact on the stock market’s reaction to EAs. Indeed, 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. Since the amount of predisclosure information cannot be observed directly, empirical work has tested this notion using various proxies for the level of predisclosure information. Empirical work has largely found evidence in support of the proposed inverse relationship (i.e. Atiase (1985), Lobo and Mahmoud (1989), Dempsey (1989), Shores (1990), Pope and Inyangete (1992) and Christensen, Smith and Stuerke (2004))

While numerous variables have been used to proxy for predisclosure information, 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. We will examine the relationship between predisclosure information and information content in EAs using these two proxies for the amount of predisclosure information. We measure firm size as both the market value of equity the day before the event window and the natural logarithm of
this market value. The number of analysts following a firm is taken from the I/B/E/S database. For EAs with no IBES data we assume that zero analysts follow the firm.

The predisclosure information hypothesis only pertains to the size of the market’s reaction, and provides no guidance as to the expected sign of the abnormal returns. An examination of the relationship between firm size and cumulated abnormal returns, CARs, will therefore not provide insight to 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. 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 (i.e. Atiase (1985) and Pope and Inyangete (1992)). The second approach examines how predisclosure information affects the earnings response coefficient (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. 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)).
3.3.2 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, Hagerman, Griffin and Zmijewski (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 the International Brokerage Estimate System (IBES)\(^2\) as estimates of the market’s expectation of earnings. Generally our measure of unexpected earnings can be written as

\[
UE = \frac{\text{actual EPS} - \text{forecast EPS}}{\text{deflator}}
\]

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 $\text{deflator} = 1$, which corresponds to using no deflator. The second deflator that we will use is $|\text{forecast EPS}|$. 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 be tested using tests of the correlation coefficient. Again this will be done using tests based on both the PPM and SRO correlation coefficients.

4 Data

The sample is constructed from firms listed on the CSE on April 17, 2002. 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. New Danish accounting standards went into effect in 2002, replacing the previous accounting standards effective as of 1997. Thus, it can be assumed that
EAs in the period 1998-2002 were reported under the same accounting standards and therefore congruent. To avoid any influence from the introduction of new accounting standards, and since the EA dates must be collected manually, we construct a 3 year sample centered in this period. We therefore extract the EA dates for the above companies in the period 1999 to 2001 from Stockwise, which is CSE’s database of stock exchange announcements. This results in a sample consisting of 158 companies and 507 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 153 companies and 491 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 “minimal” restrictions require 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 317 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 149 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. Datastream is also used to collect the market index, Carnegie Denmark Total. The analysts’ forecasts used in the study are consensus forecasts from the International Brokerage Estimate System (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.

5 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.

Insert Table 1 here

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.
5.1 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 2.

Insert Table 2 here

The table illustrates without a doubt that the EAs contain information. The market experiences large price reactions on the day of the announcement and even larger reactions 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 they are almost identical 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 3.

Insert Table 3 here

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 2 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.

5.1.1 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. Finally, given the evidence of nonnormality in table 1 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 2 and 3. Such a comparison is not as straightforward as one might first assume, since we must take into consideration the behavior of the test statistic \( Z_U \) from (3) when the sample size increases. Increasing the sample size from 149 to 317 causes the denominator in (3) to increase by a factor of 1.46. 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 2.13 (\( \approx \frac{317}{149} \)). 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 1.46. From Table 2 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 between 1.52 and
1.79 depending on the return allocation procedure used. We can therefore draw
the conclusion that the information content of EAs seems to increase when the
restrictions are relaxed.

A possible explanation of this result can be found by noting that the relax-
ation of the trading frequency restrictions causes the average market value of
equity to drop from 9.6 million DKK to 4.5 million DKK. This indicates that a
larger proportion of small firms are now included in the sample. 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 infor-
mation content of EAs for small firms should be larger than that for large firms,
which is consistent with our findings. We will test this hypothesis in section
5.2.1, and in that connection return to it’s validity as an explanation of the
above result.

To examine the effect of different trading frequency restrictions on the av-
erage abnormal returns, we now instead turn to Table 3. From this table it
is evident that both panels exhibit average abnormal returns which are signi-
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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, Hughes and Ricks (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 very subjective. Instead 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.

All in all there are 217 other announcements in the event window. However,
since a given company can have more than one announcement in the event window, these 217 announcements only pertain to 145 EAs. These EAs are deleted leaving a sample of 172 EAs. Table 4 depicts all 217 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. One exception to this, is the announcement of a change in the management, which only seems to occur after the EA.

Insert Table 4 here

The results of removing EAs with other announcements in the event window are seen in Table 5. 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 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 $Z_{Ut}$ from (3) by a factor of 0.74. A comparison of Table 5 with Table 2 reveals that the reductions are in fact much greater. Cumulating the test statistic over all event days gives a reduction of 0.48, indicating that a proportion of the above found information content of EAs was in fact attributable to the presence of concurrent disclosures.

Insert Table 5 here

Comparing Table 5 with Table 2, we see that there are now less days with a significant test statistic. The market’s reaction time to EAs is in reality shorter then we were led to believe in Table 2. 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 6 days is in accordance with an efficient market.

From Table 5 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 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. With this in mind the attempts made at explaining the information content in the next section will focus on this data set with minimal trading frequency restrictions and exclusion of EAs with concurrent disclosures, since it is free of the market’s reaction to these.

**Nonparametric tests**

Given the evidence of nonnormality of abnormal returns in table 1, 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 the 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 final 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 5 and the test statistics will therefore not be presented here. Evidence of information content is found for days -1 through 2 and both nonparametric tests find significant positive abnormal returns on day 0.

5.1.2 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 and whether the testing methodology is parametric or nonparametric.

5.2 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.

5.2.1 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 6 for \( U_{j,t} \) cumulated over different intervals of the event window, denoted
as CU.

\textbf{Insert Table 6 here}

From the table we see that several of the correlations are significantly different from zero at a 5% 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 (for example Atiase (1985) and Dempsey (1989)) and the UK (for example 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 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 the results from Christensen et al. (2004) are interesting. They find that when predisclosure information is more directly controlled for, there exists a positive relationship between information content on the one hand and firm size and number of analysts following a firm on the other. This seems to indicate 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. 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. This positive effect could result for a number of reasons. Perhaps the market is simply less interested in small firms, and therefore in essence underreacts to the information content of small EAs. It could also reflect that the quality of EAs from small firms is poor, resulting in a larger reaction to EAs from large firms.

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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 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 findings 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 section 5.1.1 that these were associated with an information content. If these disclosures are more common for small firms than large, this would lead to the found increased information content. An examination of the disclosures reveals that this is not the case. Approximately half 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. Careful examination of the data reveals that there are in fact two EAs with concurrent disclosures that the market perceives as having a large information content and reacts strongly towards. These two observations are only included when the trading frequency restrictions are relaxed. Deleting them from this sample, we find evidence of a decrease in the information content when the trading frequency restrictions are relaxed. 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.

5.2.2 Unexpected earnings

Tables 7 and 8 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% significance level, we see that the naive model performs better than the IBES model using PPM correlation coefficients, while the opposite seems to be the case when SRO correlation coefficients are used. Additionally, the lack of robustness with regard to choice of deflator and cumulation period of abnormal returns is striking. Based on the evidence presented, it therefore seems far from clear cut which, if any, of the models provides the best proxy for unexpected earnings.

Insert Tables 7 and 8 here

In an attempt to explain these puzzling results, it is useful to examine some of the proposed sources of financial analyst forecast’s superiority. Brown, Hagerman, Griffin and Zmijewski (1987b) find that they can attribute part of the
superiority of 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. With this in mind, an examination of the timeliness of our analysts’ forecasts reveals that there are a few which deviate from the rest with respect to their timeliness. Including these in the sample therefore in effect biases the results against the IBES model. It is of interest to examine how the models perform without these observations, so we delete any observations where the consensus analyst forecast available at the EA date is more than a month old. This only removes 7 observations, but generates remarkably different results that are presented in Tables 9 and 10 for the naive and IBES model, respectively.

Insert Tables 9 and 10 here

Again we find that an evaluation based on the PPM correlation coefficient reveals that the naive model performs marginally better than the IBES model. However, the removal of the less recent consensus analyst forecasts has had a remarkable effect on the performance of the IBES model when measured by the significance of the SRO correlation coefficient, and here the IBES model outperforms the naive model without a doubt. One could of course question whether this improvement in the performance of the IBES model is caused by its increased timeliness or the removal of 7 possibly outlier observations. Since the effect of the removal of these observations does not seem to be nearly as large for the naive model, it seems most likely that the improvement in the IBES model can be attributed to the increased timeliness of the analysts’ forecasts. Since the SRO correlation coefficient requires no distributional assumptions, while retaining an efficiency of 91.2% if the distribution is in fact bivariate normal (see Hotelling and Pabst (1936)), we will rely mainly on the results based on the SRO correlation coefficient. We can therefore conclude that the IBES model provides a better proxy for unexpected earnings in Denmark than the naive model, and this superiority is enhanced when only recent forecasts are
used.

From Tables 8 and 10 it is clear that the performance of the IBES model is very dependent on the source of actual eps. In particular, it performs poorly when actual eps are drawn from the I/B/E/S database. This is in accordance with the aforementioned findings of Philbrick and Ricks (1991). It is also of interest to examine the impact of using different deflators on the performance of the model. Again Tables 8 and 10 clearly indicate 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 we have examined the IBES model based on actual earnings data from Account Data 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 the conclusion we first note that the tables in this section have shown that the number of observations underlying the 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 97 observations. The results are consistent with the above conclusions and hence will not be depicted. Additionally, correlations are calculated for a data set containing EAs with concurrent disclosures. Although the results support our conclusion of the superiority of the IBES model both models perform poorly. This is as could be expected given that we have found evidence indicating that the concurrent disclosures also have information content. Part of the abnormal returns can therefore be attributed to these announcements, distorting the relationship between unexpected earnings and abnormal returns. Our conclusion of the superiority of the IBES model over the naive model therefore seems robust.
towards these alterations.

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 abnormal returns cumulated over different periods of the event window 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 IBES model is therefore based on actual earnings data from Account Data and uses market value as the deflator. The unexpected earnings measure from the naive model uses actual earnings from the I/B/E/S database and the absolute value of last years earnings as the deflator. We will not present the results of the regression here, but simply comment on them in the following.

All the coefficients are significant when the abnormal returns are cumulated over either the day of the EA and the day following or the entire event window. Interestingly, based on the adjusted $R^2$ from two models that include the IBES and naive model separately, it seems that the naive model performs better than the IBES model. This is consistent with our above findings based on the PPM correlation coefficient, and can be a result of the more restrictive nature of the multivariate regression compared to the tests based on the SRO correlation coefficient. When unexpected earnings from both of the models are included in a regression together, we find that the two proxies for unexpected earnings do in fact have explanatory power over each other, since both coefficients in the regression are significant. This finding is consistent with a possible measurement error problem associated with using a proxy for unexpected earnings. If
regressions are conducted on a proxy for unexpected earnings and other variables, then estimates of the coefficients will be inconsistent if the measurement error from the proxy is correlated with one of the other variables. This problem can be alleviated by including both proxies for unexpected earnings in the regression. Brown et al. (1987a) provide a thorough investigation of this issue. Finally, although the adjusted $R^2$ is fairly high compared to similar studies (see Lev (1989) for a review), a large part of the abnormal returns are still left unexplained.

6 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 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 6 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 relationship 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, we align our results with the existing literature by interpreting them as evidence of a low level of predisclosure information in Denmark. 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). It is interesting to note that our conclusions regarding the best proxy are rather dependent on the testing methodology used. This indicates that perhaps the contradictory results from similar studies of proxies for unexpected returns are due to methodological differences.

Notes

1From 1999 to 2001 1 EURO was on average equal to 7.45 DKK with only minor fluctuations from this average value.

2The 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.

3Since this construction method excludes firms that were delisted during the period, it potentially induces survivorship bias in our results. From delisting records for the period it is estimated that the number of excluded EAs is small. Indeed, if the inclusion of these EAs were to change the results markedly one would have to wonder if this was a reflection of EAs in general or circumstances specific to firms on the verge of delisting. Regardless, our results should be viewed in light of this exclusion of delisted firms.
References


Table 1: Descriptive statistics for abnormal returns

<table>
<thead>
<tr>
<th>Event Day</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Jarque-Bera</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A. Strict Restrictions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-5</td>
<td>-0.1082</td>
<td>0.0736</td>
<td>-0.0001</td>
<td>0.0264</td>
<td>-0.7101</td>
<td>3.1649</td>
<td>73.702*</td>
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<tr>
<td>-4</td>
<td>-0.0680</td>
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<td>0.0005</td>
<td>0.0228</td>
<td>0.1358</td>
<td>1.7975</td>
<td>20.241*</td>
</tr>
<tr>
<td>-3</td>
<td>-0.0919</td>
<td>0.0838</td>
<td>0.0039</td>
<td>0.0269</td>
<td>0.1569</td>
<td>1.7050</td>
<td>18.409*</td>
</tr>
<tr>
<td>-2</td>
<td>-0.0637</td>
<td>0.0987</td>
<td>0.0044</td>
<td>0.0252</td>
<td>0.4253</td>
<td>1.9300</td>
<td>27.235*</td>
</tr>
<tr>
<td>-1</td>
<td>-0.1362</td>
<td>0.0969</td>
<td>0.0021</td>
<td>0.0299</td>
<td>-1.0797</td>
<td>5.5213</td>
<td>215.287*</td>
</tr>
<tr>
<td>0</td>
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<td>0.0853</td>
<td>-0.0033</td>
<td>0.0420</td>
<td>-1.2381</td>
<td>2.1218</td>
<td>65.131*</td>
</tr>
<tr>
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<td>-0.0551</td>
<td>1.5690</td>
<td>15.152*</td>
</tr>
<tr>
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<td>0.1454</td>
<td>0.0014</td>
<td>0.0365</td>
<td>0.6209</td>
<td>2.9873</td>
<td>64.106*</td>
</tr>
<tr>
<td>3</td>
<td>-0.0967</td>
<td>0.1375</td>
<td>0.0050</td>
<td>0.0319</td>
<td>0.7744</td>
<td>2.5114</td>
<td>53.326*</td>
</tr>
<tr>
<td>4</td>
<td>-0.0932</td>
<td>0.1325</td>
<td>-0.0027</td>
<td>0.0317</td>
<td>0.8308</td>
<td>4.0471</td>
<td>117.234*</td>
</tr>
<tr>
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<td>-0.1437</td>
<td>0.1181</td>
<td>0.0011</td>
<td>0.0286</td>
<td>-0.2572</td>
<td>6.1616</td>
<td>234.158*</td>
</tr>
<tr>
<td>Panel B. Minimal Restrictions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-5</td>
<td>-0.1420</td>
<td>0.0916</td>
<td>-0.0019</td>
<td>0.0264</td>
<td>-1.2231</td>
<td>6.0489</td>
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<tr>
<td>-4</td>
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<td>0.0230</td>
<td>-1.3658</td>
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<tr>
<td>-3</td>
<td>-0.0919</td>
<td>0.3249</td>
<td>0.0047</td>
<td>0.0315</td>
<td>3.7546</td>
<td>34.2615</td>
<td>16146.860*</td>
</tr>
<tr>
<td>-2</td>
<td>-0.1619</td>
<td>0.1267</td>
<td>0.0010</td>
<td>0.0278</td>
<td>-0.7298</td>
<td>8.7734</td>
<td>1038.233*</td>
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<td>0.0330</td>
<td>-1.4751</td>
<td>10.5650</td>
<td>1579.239*</td>
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<td>0</td>
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<td>0.0008</td>
<td>0.0408</td>
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<td>3.1558</td>
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<tr>
<td>1</td>
<td>-0.5095</td>
<td>0.1839</td>
<td>-0.0034</td>
<td>0.0562</td>
<td>-3.0262</td>
<td>25.3567</td>
<td>8919.643*</td>
</tr>
<tr>
<td>2</td>
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<td>0.2449</td>
<td>0.0004</td>
<td>0.0416</td>
<td>-0.9503</td>
<td>15.3560</td>
<td>3142.361*</td>
</tr>
<tr>
<td>3</td>
<td>-0.2168</td>
<td>0.1375</td>
<td>-0.0002</td>
<td>0.0363</td>
<td>-1.2341</td>
<td>10.4320</td>
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<td>4</td>
<td>-0.2823</td>
<td>0.2179</td>
<td>-0.0023</td>
<td>0.0376</td>
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<td>18.1051</td>
<td>4354.776*</td>
</tr>
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<td>0.3378</td>
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<td>0.0356</td>
<td>2.9977</td>
<td>27.2224</td>
<td>10108.480*</td>
</tr>
</tbody>
</table>

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 149, while Panel B presents results when the minimal trading frequency restrictions are used leading to a sample size of 317. Jarque-Bera denotes the Jarque-Bera test for normality and * denotes that it rejects normality at a 1% significance level.
Table 2: Test of information content

<table>
<thead>
<tr>
<th>Event Day</th>
<th>Strict restrictions</th>
<th>Minimal restrictions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lumped</td>
<td>Uniform</td>
</tr>
<tr>
<td>-5</td>
<td>0.1340</td>
<td>0.6644</td>
</tr>
<tr>
<td>-4</td>
<td>-0.3700</td>
<td>-0.1439</td>
</tr>
<tr>
<td>-2</td>
<td>1.7611</td>
<td>1.9341</td>
</tr>
<tr>
<td>-1</td>
<td>2.8993*</td>
<td>3.0848*</td>
</tr>
<tr>
<td>0</td>
<td>21.3897*</td>
<td>21.8180*</td>
</tr>
<tr>
<td>1</td>
<td>30.6885*</td>
<td>31.4970*</td>
</tr>
<tr>
<td>3</td>
<td>8.5209*</td>
<td>9.0259*</td>
</tr>
<tr>
<td>5</td>
<td>4.8967*</td>
<td>5.1287*</td>
</tr>
</tbody>
</table>

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 149, while columns 5 to 7 present results when the minimal trading frequency restrictions are used leading to a sample size of 317. Lumped, Uniform, and T-to-T denote the lumped, uniform, and trade-to-trade return allocation procedures, respectively.

* denotes significant at a 5% significance level.

Table 3: Average abnormal returns

<table>
<thead>
<tr>
<th>Event Day</th>
<th>Strict restrictions</th>
<th>Minimal restrictions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lumped</td>
<td>Uniform</td>
</tr>
<tr>
<td>-5</td>
<td>-0.00013</td>
<td>-0.00009</td>
</tr>
<tr>
<td>-4</td>
<td>0.00043</td>
<td>0.00048</td>
</tr>
<tr>
<td>-3</td>
<td>0.00388*</td>
<td>0.00389*</td>
</tr>
<tr>
<td>-2</td>
<td>0.00440*</td>
<td>0.00441*</td>
</tr>
<tr>
<td>-1</td>
<td>0.00203</td>
<td>0.00211</td>
</tr>
<tr>
<td>0</td>
<td>-0.00325</td>
<td>-0.00322</td>
</tr>
<tr>
<td>1</td>
<td>-0.00440</td>
<td>-0.00432</td>
</tr>
<tr>
<td>2</td>
<td>0.00136</td>
<td>0.00141</td>
</tr>
<tr>
<td>3</td>
<td>0.00501*</td>
<td>0.00508*</td>
</tr>
<tr>
<td>4</td>
<td>-0.00262</td>
<td>-0.00258</td>
</tr>
<tr>
<td>5</td>
<td>0.00100</td>
<td>0.00104</td>
</tr>
</tbody>
</table>

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 149, while columns 5 to 7 present results when the minimal trading frequency restrictions are used leading to a sample size of 317. Lumped, Uniform, and T-to-T denote the lumped, uniform, and trade-to-trade return allocation procedures, respectively.

* denotes that the average abnormal returns are significant at a 5% significance level, when significance is tested using test statistic $J_t$ from (5).
Table 4: Concurrent disclosures in the event window

<table>
<thead>
<tr>
<th>Announcement regarding</th>
<th>Event day</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-5</td>
</tr>
<tr>
<td>Annual general meeting</td>
<td>2</td>
</tr>
<tr>
<td>Acquisition/sale of share in firm</td>
<td>1</td>
</tr>
<tr>
<td>Annual report</td>
<td>-</td>
</tr>
<tr>
<td>Notification from major shareholder</td>
<td>3</td>
</tr>
<tr>
<td>Supplement/correction to EA</td>
<td>-</td>
</tr>
<tr>
<td>Management change</td>
<td>-</td>
</tr>
<tr>
<td>Transfer to/remove from observation list</td>
<td>-</td>
</tr>
<tr>
<td>Date for EA</td>
<td>6</td>
</tr>
<tr>
<td>Strategic relations</td>
<td>1</td>
</tr>
<tr>
<td>Large order/contract for delivery</td>
<td>1</td>
</tr>
<tr>
<td>Investor relations</td>
<td>-</td>
</tr>
<tr>
<td>Financial calender</td>
<td>-</td>
</tr>
<tr>
<td>Change in capital</td>
<td>-</td>
</tr>
<tr>
<td>Own shares</td>
<td>-</td>
</tr>
<tr>
<td>Comment to media coverage</td>
<td>1</td>
</tr>
<tr>
<td>Large investment</td>
<td>-</td>
</tr>
<tr>
<td>Request for suspension</td>
<td>-</td>
</tr>
<tr>
<td>Fusion</td>
<td>-</td>
</tr>
<tr>
<td>Traffic statistic/correction</td>
<td>-</td>
</tr>
<tr>
<td>Extraordinary general meeting</td>
<td>-</td>
</tr>
<tr>
<td>Credit rating</td>
<td>-</td>
</tr>
<tr>
<td>No quarterly reports</td>
<td>-</td>
</tr>
<tr>
<td>Convertible bonds</td>
<td>-</td>
</tr>
<tr>
<td>Juridical decisions</td>
<td>-</td>
</tr>
<tr>
<td>Rationalizations</td>
<td>-</td>
</tr>
<tr>
<td>Articles of association</td>
<td>-</td>
</tr>
<tr>
<td>Strengthens financial preparedness</td>
<td>-</td>
</tr>
<tr>
<td>Starting clinical trials sooner</td>
<td>-</td>
</tr>
</tbody>
</table>

All | 15 | 6 | 17 | 6 | 17 | 61 | 28 | 15 | 6 | 27 | 19 | 217 |
Table 5: Minimal restrictions without concurrent nonearnings disclosures

<table>
<thead>
<tr>
<th>Event Day</th>
<th>Information Content</th>
<th>Average abnormal returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>-5</td>
<td>-2.2372*</td>
<td>-0.00157</td>
</tr>
<tr>
<td>-4</td>
<td>-1.4818</td>
<td>-0.00090</td>
</tr>
<tr>
<td>-3</td>
<td>0.1539</td>
<td>0.00389</td>
</tr>
<tr>
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</tr>
<tr>
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<td>7.8040*</td>
<td>0.00030</td>
</tr>
<tr>
<td>0</td>
<td>13.2302*</td>
<td>0.00565*</td>
</tr>
<tr>
<td>1</td>
<td>19.5461*</td>
<td>0.00430</td>
</tr>
<tr>
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<td>11.0111*</td>
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</tr>
<tr>
<td>3</td>
<td>8.3518*</td>
<td>0.00038</td>
</tr>
<tr>
<td>4</td>
<td>10.3396*</td>
<td>-0.00015</td>
</tr>
<tr>
<td>5</td>
<td>0.0673</td>
<td>-0.00312</td>
</tr>
</tbody>
</table>

Notes:
The results are based on the use of minimal trading frequency restrictions and the trade-to-trade return allocation procedure. In addition earnings announcements with concurrent disclosures in the event window are deleted, leading to a sample size of 172. Column 2 presents the test statistic $Z_{it}$ from (3). Column 3 presents average abnormal returns, whose significance is tested using test statistic $J_i$ from (5). * denotes significant at a 5% significance level.
Table 6: Correlations between predisclosure information and information content

<table>
<thead>
<tr>
<th></th>
<th>Panel A. With concurrent disclosures</th>
<th></th>
<th>Panel B. Without concurrent disclosures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n=317</td>
<td></td>
<td>n=172</td>
</tr>
<tr>
<td>CU[0;0]</td>
<td>estimate 0.0769 0.1453 0.1082 0.2995 0.02673</td>
<td></td>
<td>CU[0;0] estimate 0.0239 0.1258 0.1839 0.2337 0.2682</td>
</tr>
<tr>
<td></td>
<td>prob &gt;</td>
<td>r</td>
<td>0.1719 0.0096 0.0544 &lt;0.0001 &lt;0.0001</td>
</tr>
<tr>
<td>CU[0;1]</td>
<td>estimate 0.0104 0.0771 0.0906 0.2936 0.3153</td>
<td></td>
<td>CU[0;1] estimate -0.0358 0.1250 0.1640 0.2460 0.2967</td>
</tr>
<tr>
<td></td>
<td>prob &gt;</td>
<td>r</td>
<td>0.8531 0.1711 0.1072 &lt;0.0001 &lt;0.0001</td>
</tr>
<tr>
<td>CU[-5;5]</td>
<td>estimate 0.0029 0.0566 0.0350 0.2211 0.1817</td>
<td></td>
<td>CU[-5;5] estimate -0.0276 0.0218 0.0424 0.1560 0.1720</td>
</tr>
<tr>
<td></td>
<td>prob &gt;</td>
<td>r</td>
<td>0.9595 0.3152 0.5343 &lt;0.0001 0.0012</td>
</tr>
<tr>
<td>CU[0;5]</td>
<td>estimate -0.0003 0.0476 0.0571 0.2439 0.2121</td>
<td></td>
<td>CU[0;5] estimate -0.0326 0.0424 0.0653 0.1926 0.2151</td>
</tr>
<tr>
<td></td>
<td>prob &gt;</td>
<td>r</td>
<td>0.9953 0.3979 0.3110 &lt;0.0001 0.0001</td>
</tr>
</tbody>
</table>

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 7: Correlation between naive model unexpected earnings and CARs

<table>
<thead>
<tr>
<th></th>
<th>I/B/E/S</th>
<th></th>
<th>Account Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>none</td>
<td></td>
<td>MV</td>
</tr>
<tr>
<td><strong>Panel A. PPM correlation coefficient</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAR[0:1]</td>
<td>estimate</td>
<td>0.1442</td>
<td>0.2595</td>
</tr>
<tr>
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<td>prob &gt;</td>
<td>r</td>
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</tr>
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*Notes:* Based on the data set with minimal trading frequency restrictions and no earnings announcements with concurrent disclosures. 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 columns 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 deflators absolute value of forecast and market value, respectively.
Table 8: Correlation between IBES model unexpected earnings and CARs

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<td><strong>Panel A. PPM correlation coefficient</strong></td>
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<tr>
<td>prob &gt;</td>
<td>prob &gt;</td>
<td>estimate</td>
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**Notes:**
Based on the data set with minimal trading frequency restrictions and no earnings announcements with concurrent disclosures. 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 columns 6-8 use actual eps from Account Data. None denotes no use of a deflator in the calculation of unexpected earnings. \(|E[\text{eps}]||\) and MV denote the deflators absolute value of forecast and market value, respectively.

49
Table 9: Correlations between naive model unexpected earnings and CARs

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<td><strong>Panel A. PPM correlation coefficient</strong></td>
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<td>0.3598</td>
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<td>111</td>
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</tbody>
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| **Panel B. SRO correlation coefficient** |      |        |    |      |        |    |
| estimate             | 0.1570 | 0.1885 | 0.1274 | 0.0968 | 0.1323 | 0.0799 |
| prob > [r]           | 0.0998 | 0.0476 | 0.1889 | 0.2419 | 0.1090 | 0.3446 |
| n                    | 111   | 111   | 108 | 148 | 148 | 142 |
| estimate             | 0.1700 | 0.1747 | 0.1706 | 0.1485 | 0.1809 | 0.1361 |
| CAR[-5;5]            | prob > [r] | 0.0745 | 0.0667 | 0.0776 | 0.0717 | 0.0278 | 0.1062 |
| n                    | 111   | 111   | 108 | 148 | 148 | 142 |
| estimate             | 0.1058 | 0.1319 | 0.1246 | 0.0763 | 0.1097 | 0.1022 |
| CAR[0;5]             | prob > [r] | 0.2691 | 0.1678 | 0.1988 | 0.3564 | 0.1843 | 0.2260 |
| n                    | 111   | 111   | 108 | 148 | 148 | 142 |

**Notes:**
Based on data with minimal trading frequency restrictions, no concurrent disclosures, and financial analyst forecasts from the month preceding the EA. 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 columns 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 deflators absolute value of forecast and market value, respectively.
Table 10: Correlations between IBES model unexpected earnings and CARs

<table>
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<tr>
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<td><strong>Panel A. PPM correlation coefficient</strong></td>
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*Notes:*
Based on data with minimal trading frequency restrictions, no concurrent disclosures, and financial analyst forecasts from the month preceding the EA. 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 columns 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 deflators absolute value of forecast and market value, respectively.