Short-term Post-Earnings Announcement Effects

by

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Abstract

Stock prices usually react quickly to new information released at an earnings announcement. However, sometimes stock prices seem to continue to move over a period of time after the initial effect. Such movements are called post-earnings announcement effects. The effects can take two shapes, either the price moves in the same direction as the initial reaction (a momentum) or it moves in the opposite direction (a reversal). The existence of such effects is in violation of the Efficient Markets Hypothesis and is called an anomaly. This thesis investigates the post-earnings announcement phenomenon for Swedish stocks during 10 years from 1997 to 2007 by using a trading strategy beginning on the day after the earnings announcement. Quintile portfolios are formed using two metrics: initial abnormal return (IAR) and initial abnormal volume (IAV). These metrics are used for sorting the stocks into quintile portfolios. A market–neutral position is created using a long/short strategy and positions are held for up to 60 trading days. These trading strategies earn annualized abnormal returns of about 11% using on the IAR metric and about 8% using the IAV metric. A joint strategy that uses both metrics generate more than three times as much in annualized abnormal return. Although these findings suggest that post-earnings announcement effects are present in the Swedish stock market, the evidence is not found to be robust enough to warrant a formal rejection of the Efficient Market Hypothesis.

I would like to thank to my supervisor Ulf Axelson for his valuable advice and comments.

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1 Introduction

The behavior of stock prices around earnings announcements has been a frequently investigated financial phenomenon for decades. A pioneering study by Ball and Brown (1968) found that stock prices on average drift upward (downward) after an earnings announcement if the earnings are unexpectedly positive (negative). This apparent violation of market efficiency associated with earnings announcements has since been confirmed by numerous other studies, e.g. Foster, Olsen and Shevlin (1984) and Bernard and Thomas (1989). Subscribers to the efficient markets hypothesis have made attempts to explain the phenomenon as a result of inadequate risk adjustment or other flaws in research methodology, but they have only been partially successful (see e.g. Fama 1998). As the phenomenon has proven to be persistent over time and economically significant, researchers have decided to call it an anomaly – a quite rare title in the field of finance. With the failure of the efficient markets theory in explaining the anomaly, researchers have presented several alternative explanations within the rapidly expanding field of behavioral finance. All of these explanations have in common that investors behave irrationally in some respect (see Hong and Stein 1997 for an example).

This thesis aspires to investigate post-earnings announcement effects for Swedish stocks listed on the Stockholm Stock Exchange. The focus of the thesis is to establish whether or not the efficient market hypothesis holds in the short term (for periods up to 60 days) after earnings announcements. Under the efficient market hypothesis, prices should immediately adjust to reflect any new information and thus there should be no drift, either positive or negative, in prices after the announcement. If systematic abnormal returns can be made after prices have adjusted to the new information, then that would be a violation of the hypothesis. To give the efficient market hypothesis as much room as possible, portfolios will not be formed until the day after the announcement. In other words, the market will have sufficient time to incorporate the new information. If the hypothesis does not hold and post-earnings announcement effects are found, I will investigate how they relate to the nature of the information released at the earnings announcement by considering metrics related to the information as such, rather than metrics relating to properties of the reporting company such as for example size or analyst coverage. The metrics I will use are the initial abnormal return and the initial abnormal trading volume that can be observed on the announcement day.

Previous research on the determinants of post-earnings announcement effects has focused mainly on earnings metrics published at the time of the announcement and how that information deviates from analysts' consensus estimates. However, less attention have been directed to other non-earnings metrics and unexpected information which is not explicitly published in a written earnings report or press-release. In this thesis, I look at price changes on the announcement day as a proxy for *all* value-relevant information released in connection with earnings announcements. In contrast, earnings metrics merely report historical performance and does not contain any information about future earnings capacity. For example, there could be event-specific information about the outlook of the company or even hints and pieces of information revealed in replies to questions at the press conference. Furthermore, it has become increasingly common to hold earnings-related conference calls that are typically within a few hours of the earnings announcement, and it is not unusual for analysts to obtain "soft" information about future firm performance in private discussions with the firm management. By using price changes as an arguably more complete measure of information, this thesis aims to uncover new insights about earnings announcement effects.

Change in trading volume has been investigated to a lesser extent in relation to earnings announcements. In this thesis, I will investigate how the earnings announcement effect is related to changes in trading volume on the announcement day. Intuitively, trading volume can be thought of as a proxy for the amount of new information released since, all other things equal, the more (less) new information that comes out of an earnings announcement, the more (less) reason for investors to revise their decision to own/not own the stock. This could in turn lead to a decision to buy or sell the stock after taking into account transaction costs, which could lead to higher (lower) trading volume. Another way to think about is as a proxy for how difficult the new information is to interpret. The more (less) new information that is released at an earnings announcement, the more (less) likely it will be that investors disagree about something in the information and arrive at different decisions whether to own/not own the stock.

The main finding of this thesis is evidence for post-earnings announcement momentum and reversal effects in the Swedish stock market for the period 1997 to 2007. These effects are related to both abnormal return and abnormal volume on the announcement day. The abnormal returns earned by strategies that exploit these effects are in most cases consistent and economically meaningful, which seem to indicate that markets are not efficient. Both initial abnormal return and abnormal volume were found to be able to produce abnormal returns when used as separate metrics for different trading strategies. I have also found that they can be used jointly to create even higher returns, although they are not completely independent of each other.

This thesis is organized as follows. In section 2, related research is discussed and a suggestion is presented for how the two metrics abnormal return and abnormal volume could be related (in theory) to post-earnings announcement effects. Section 3 describes the sample and the empirical methodology while section 4 describes results and performs some robustness tests. Finally, conclusions on how the empirical results match up with theory are presented in section 5.

NB: The number of figures and tables in this thesis can be quite overwhelming. To help the reader keep track of things, I have tried to label them and included indexes of tables and figures (found on page iii). The most space-consuming tables were moved to the Appendix.

2 Background to the research problem

In this section I will put this thesis into context by presenting a theoretical framework consisting of selected sources of previous research related to the subject of reactions to earnings announcements. First, a definition of post-earnings announcement effects is presented. Second, research related to this thesis is reviewed together with some of the main findings related to post-earnings announcement effects in general to provide the reader with some background. Third, I will discuss the tests I want to perform and what I expect to find.

2.1 Definition of post-earnings announcement effects

By post-earnings announcement effects, I will in this thesis refer to the phenomenon of stock prices that, after initial reactions to news from earnings announcements, continues to move for a period of time, so that systematic returns can be made over and above what can be normally expected given the relevant risks-characteristics of a particular stock. This means that investors can make risk-adjusted profits by repeatedly buying or short-selling the stock. If the stock price continues to move more than we would normally expect in a positive (negative) direction after an initial positive (negative) reaction to the earnings announcement news, this is termed an underreaction or momentum effect. This is in reference to the idea that the market did not immediately price all the new value-relevant information into the stock price. If the stock price moves in a positive (negative) direction more than we would normally expect after an initial negative (positive) reaction to the earnings announcement news, this is termed an overreaction or reversal. This pertains to the notion that the market initially adjusted the stock price over and above what was motivated by the new value-relevant information being released.

Notice that post-earnings announcement effect is defined here in terms of the initial price reaction on the day of the earnings announcement. With perfect markets, this initial reaction should adequately reflect the value of any new information and no momentum or reversal effects in returns should be observed. Any subsequent momentum or reversal is therefore related to the initial reaction. However, it may very well be that the stock price would have moved anyway if there had not been an earnings announcement on that particular day. Therefore, to be able to label price reactions as over-or underreactions we must first define what the expected normal movement of the stock price is: the normal return on that day. By adjusting the raw returns by filtering out this normal return we end up with abnormal returns. In this thesis, I will refer to the abnormal return on an earnings announcement day as the initial abnormal return (*IAR*).

2.2 Related research

Ball and Brown (1968) made the initial discovery of earnings announcement effects in their study of market reactions to forecasting errors. The study is based on data for US stocks over a period of two decades from 1946 to 1966. The main idea is that reporting unexpectedly high (low) earnings creates subsequent positive (negative) abnormal returns. The metric used for portfolio formation is the difference between reported earnings and forecasted earnings one year before the announcement date and a market model is used to estimate normal returns. The authors find evidence of a momentum – or rather a more long-term drift - which starts one year before the announcement. The short-term momentum in the month of announcement and the six months afterwards is smaller than in the twelve months preceding the announcement. The authors offer an explanation for this: the market continuously receives information about earnings, gradually decreasing uncertainty about forecast errors as the announcement date approaches and the stock price is adjusted accordingly. As a consequence, there is little unknown information in the actual earnings announcement report, which in turn leads to only marginal changes in the stock price after the announcement.

Foster, Olsen and Shevlin (1984) investigate earnings announcement effects by forming portfolios using several different metrics to approximate unexpected earnings. Data for US stocks over a ten-year period from 1971 to 1981 is used and normal returns are estimated using a simple average from size deciles. The authors find that the metric that performs the best is the difference between actual and forecasted earnings divided by the standard deviation of forecasts. This metric called standardized unexpected earnings (*SUE*) has since been a commonly used proxy for unexpected earnings. The highest decile portfolio for *SUE* earned a statistically significant cumulative abnormal return of about 3% over a holding period of 60 days. A strategy with a long position in that portfolio combined with a short position in the lowest decile portfolio yielded an annualized abnormal return of about 25%. Interestingly, by running regressions on *CAR* for several explanatory variables, the authors find that firm size explains 61% of the variation in *CAR*. If everything else is equal, a small stock portfolio generates a higher *CAR* than a large stock portfolio.

Bernard and Thomas (1989) investigate the earnings announcement phenomenon for US stocks during the period 1974-1986. Normal returns are estimated as in Foster, Olsen and Shevlin's study and the metric used to approximate unexpected earnings the same *SUE* metric. The authors find that a long/short strategy in the extreme *SUE* deciles yields an abnormal return of about 4.2% over a period of 60 days after the earnings announcement or about 18% on an annualized basis. The authors note that the *CAR*s seem to be capped at a certain level and keep within "round-trip transaction costs for the small individual investor". This is taken as evidence that the momentum can be explained with transaction costs creating a sufficient impediment to trading to prevent a complete and immediate response to earnings announcements. Another plausible explanation is also presented: investors fail to assimilate serial correlations in quarterly earnings shocks. In other words, stock prices react to a component of the earnings information like it is a surprise even though it could have been predicted using past time series of earnings.

Recent research has focused on trying to find common characteristics of stocks that exhibit large momentum effects. For instance, Johnson and Schwartz Jr. (2000) extend Bernard and Thomas' line of reasoning and find evidence that momentum after earnings announcements is most pronounced and persistent where transaction costs are the highest – that is for small firms where the stocks are likely to be illiquid and bid-ask spreads high, and for firms with few or no analysts following the stock. Another example is Mikhail et al (2003) who show that analyst experience is negatively correlated to momentum. The rationale behind that result is that more experienced analysts are capable of incorporating implications of unexpected earnings information for the actual future earnings capability of a firm to a larger extent than less experienced analysts are. Characteristics pertaining to the owners of momentum-prone stocks have also been subject to investigation by several studies. The findings of Bartov et al (2000) indicate that stocks with a large proportion of institutional investors experience a smaller drift, the presumption being that such investors use relatively more sophisticated approaches to investing and hence are less likely to underreact to surprises in earnings information.

Although different flavors of the *SUE* metric is by far the most commonly used in studies of earnings announcements effects, recent studies have begun to investigate alternative ways of approximating unexpected information in earnings announcements. One interesting example is

Brandt et al (2006) who use a metric called earnings announcement return (*EAR*), which is defined as the abnormal return over a three-day window centered on the announcement date. Besides the actual earnings news, *EAR* is presumed to include unexpected information about various other items such as sales, margins, investment, and other less tangible information communicated around the earnings announcement. Using both *EAR* and *SUE* to form portfolios, a simple long/short strategy in the extreme portfolios generate abnormal returns of about 6% per annum for each of the metrics. The authors also find that these strategies are independent of each other and that a joint strategy based on the *EAR* and *SUE* metrics in combination can be used to generate abnormal returns of about 11% on an annual basis.

The link between earnings announcements and trading volume has not been explored to any great extent. However, Karpoff (1987) have found that there is general evidence of stock returns and trading volume being positively correlated: stock prices tend to go up on high volume and go down on low volume. A recent study of interest is the one by Frazzini and Lamont (2006) which examines the relation between trading volume and earnings announcement effects. The authors find that a strategy of buying all stocks that are expected to have an earnings announcement for a given month and selling short all stocks that are not expected to announce earnings yields an abnormal return of about 7% per year. This premium is found to be strongly correlated to increases in volume concentrated to earnings announcements. Apparently, stocks with high abnormal volume in past announcement periods, all other things equal, earn a higher premium during subsequent announcement periods. One plausible explanation for the rise in volume is the findings of Kandel and Pearson (1995) that differences of opinion about the meaning of new information lead to high volume around earnings announcements.

2.3 Hypotheses

The first thing I want to test is whether or not the efficient market hypothesis holds. Given the extensive findings of post-announcement effects in previous studies, I will expect to find some evidence of market inefficiency. Most previous studies have looked at data from the US, which intuitively should be a market that comes closer than the Swedish market to fulfilling the assumptions of the ideal efficient market model in terms of the number of investors, supply of capital and other matters relating to size. Therefore, I expect to find that the Swedish stock market is at least as inefficient as the US market.

One other thing I set out to investigate was if market reactions to earnings announcements can be understood better by taking into account that the market must not only price unexpected earnings figures but also other types of information, which happens to arrive at the same time. The idea is to approximate the combined value of the usual earnings information and any other value-relevant non-earnings information with the abnormal price change on the announcement day. To isolate the effect from the new information I will filter out general market movements and other price changes which are due to relevant risk factors, rather than using raw price changes. In this thesis I will refer to this filtered metric as initial abnormal return (*IAR*). Since the existence of post-announcement effects is so firmly established in previous research using earnings-related metrics like *SUE*, it seems reasonable that the market finds it at least equally difficult to price this kind of intangible information. Thus, to the extent that the *IAR* approximation is accurate as a proxy, I would expect to find evidence of post-announcement effects to a strategy based on this metric at least as large as to the *SUE* metric.

A desirable side effect of using *IAR* as a metric for portfolio formation is that it allows us to easily identify momentum (or reversal) patterns without including the *AR* on the announcement day when we accumulate the abnormal returns (exactly how this is done will be explained in detail later). For example, if we instead would have formed our portfolios by some strategy based on *SUE* and found a positive abnormal return for that portfolio, we would not be able to tell if this positive abnormal return was in fact a reversal effect from an initial negative price reaction, or a momentum effect from an initial positive price reaction.

In this thesis I will also try to see how the trading volume piece fits into the post-announcement effects jigsaw puzzle. Reasonable conclusions from the previously cited evidence are that abnormal trading volume is somehow linked to abnormal returns and that earnings announcements predictably give rise to surges in trading volume. With this in mind, there are two aspects of trading volume which makes it interesting to use as a metric for portfolio formation. The first is that volume can work as a proxy for the "amount" of new information. The logic for that is that the more new information the more likely something in it will change some investors' opinions about owning/not owning the stock, which leads to more trading. The second aspect is that volume can indicate information complexity. The more complex the information, the greater the differences in opinions among investors about the implications of the new information for the value of the stock. The stock will appear to be underpriced by some investors and overpriced by others, which should consequently lead to more trading. Intuitively, increasingly complex information could also give an advantage to owners (sellers) of the stock since the average owner of the stock probably is more familiar with the business of the company than the average non-owner.

Of course this proxy is not perfect. There are numerous other reasons for trading a stock than new information, for example rebalancing a portfolio to make it as well diversified as possible. However, I will assume that on earnings announcement dates, trading in the stock will be mostly driven by new information. To isolate earnings announcement-specific effects on volume I filter out general market-wide changes in volume from the raw change in volume on the announcement day into a metric I will refer to as initial abnormal volume (IAV). To the extent that IAV actually works as a proxy for the amount and complexity of information as described above, I expect to find evidence of post-announcement effects to a strategy based on this metric.

The presumption from the reasoning thus far would be that such effects arise when volume is abnormally high. However, from our review of previous research we have seen that there is another aspect to take into account: Volume is generally found to be positively related to market efficiency through the concept of liquidity (investors being able to buy and sell securities with low transaction costs due to bid/ask spreads). A reasonable assumption from this would be that the market is more efficient the higher the trading volume because of lower transaction costs – all other things equal. Then we would expect to find post-announcement effects when markets are the least efficient, i.e. when volume is abnormally low.

I will now try to sum up the points from the preceding discussion and then try to state what results I will expect to find.

- From empirical evidence:
  - Firms reporting good (bad) news tend to have a positive (negative) post-announcement momentum (Ball and Brown, 1968).
  - Volume is positively related to abnormal returns (Karpoff 1987).
  - Volume is positively related to disagreement among investors about the meaning of new information (Kandel and Pearson, 1995)
  - Post-earnings announcement effects is most pronounced and persistent where transaction costs are high (Johnson and Schwartz Jr., 2000)
- From intuition:
  - Approximating the value of new information with the abnormal return on the day of the announcement should incorporate more information than unexpected earnings and thus give a better chance of finding evidence of post-earnings announcement effects (if there are any).
  - Transaction costs are negatively related to volume.
  - Positive news should make non-owners more interested in buying the stock, and negative news should make owners more interested in selling the stock.
  - Disagreement among investors is positively related to the amount and complexity of information released in an earnings announcement.
  - The average stockowner's informational advantage over the average non-owner around an earnings announcement is positively related to the amount and complexity of new information released. By using this advantage investors could sell the stock before a negative momentum or sell before a reversal from positive to negative.

These items result in a matrix of expected results as illustrated in Figure 1 below.

FIGURE 1 – “EXPECTED RESULTS”

This figure tries to summarize the different factors that could be related to post-announcement effects into a simple 2×2 matrix. This is naturally not intended as a serious attempt to quantify the expected post-earnings announcement effects, but as an ad hoc way of visualizing how the the factors could interact. The two portfolio metrics, initial abnormal returns and intial abnormal volume are mapped onto the lateral and horizontal axis respectively. Each factor is awarded a point -1, 0 or +1 depending on if and how it is assumed to affect abnormal returns. High transaction costs just adds to the size of the expected effect so no points for that. The sum of points is taken as an indication of direction and size of the expected post-announcement effects.

	• Abnormally high volume • Low transaction costs • Complex/much information give an advantage to owners	• Abnormally low volume • High transaction costs • Simple/little information give no advantage to owners
• Positive abnormal returns • Positive news • Investors should buy	”Good-news” firm: +1 High volume: +1 Many investors buy the stock: +1 No advantage for investors: 0 = +3 ”Momentum”	”Good-news” firm: +1 Low volume: -1 Few investors buy the stock: -1 No advantage for investors: 0 = -1 ”Reversal”
• Negative abnormal returns • Negative news • Owners should sell	”Bad-news” firm: -1 High volume: +1 Many owners sell the stock: -1 Informational advantage to owners : -1 = -2 “Momentum”	”Bad-news” firm: -1 Low volume: -1 Few owners sell the stock: +1 No informational advantage to owners: 0 = -1 ”Momentum”

3 Data and Methodology

3.1 Sample selection

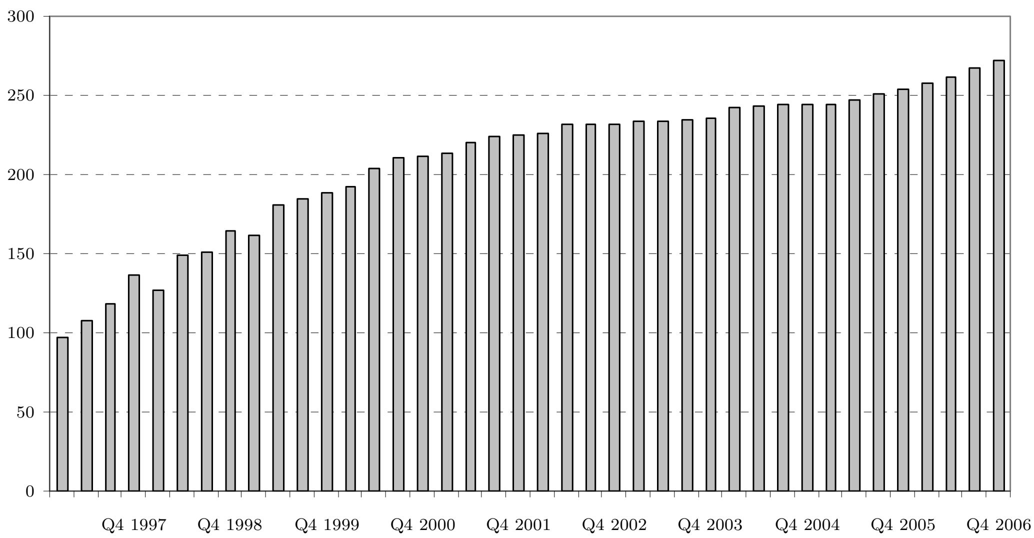
To begin with I included all 304 shares listed officially on the Stockholm Stock Exchange as of April 17 2007. The reasons for choosing to look at Swedish stocks was mainly to simplify the finding and verifying of historical announcement dates and also to avoid problems with adjusting the market risk premium in a normal return model due to differences in rates, exchange rates etc. Where several series of stocks (e.g. A and B) were listed for the same company, only the series with the highest trading volume was kept in the sample. That leaves 272 stocks. The sample period used was 10 years ranging from March 1997 to March 2007 (i.e. Q1 1997 to Q4 2006), giving a maximum of 40 quarters per stock and a total maximum of 10,880 observations.

The period of 10 years was chosen with the intention to include enough data to at least capture one full business cycle. The reason for this is that we ideally want results to be valid regardless of which state the general economy is in. As the stocks in the sample were drawn from the current list of active stocks, there is a certain survivorship bias. The main reason for not adjusting for this was that old tickers and data for delisted stocks are difficult to find. One sample constraint was that several of the stocks have not been listed for the entire period of 10 years. The number of observations (stocks) in the reporting periods increases rapidly over the first 4 years up to about 200 and then levels off somewhat (see Figure 2 below). The other main source of observations lost was missing records of announcement dates. My main source for dates was SIX Trust and the websites of individual companies. For the tests in this thesis the precision of announcement dates is crucial to achieve reliable results, which is why much effort was spent validating the dates to ensure that errors were kept at a minimum.

The final number of observations after allowing for various sources of missing data was 8,357. All time series data including stock prices, interest rates, index levels, company characteristics like book value of equity etc. was gathered through Thomson DataStream, with the sole exception of the earnings announcements dates. Daily data was used throughout the study. Closing prices was used and raw stock returns were adjusted for cash dividends per share on the actual payout dates to reflect actual stock returns.

FIGURE 2 –DISTRIBUTION OF OBSERVATIONS OVER TIME

Distribution of observations over the 40 quarters in the sample period. The total number of observations is 8,357.



3.2 Estimating normal returns

Normal returns were estimated using the following two models:

[3-factor model]: $R_{it} - R_{ft} = a_i + b_i\,(R_{mt} - R_{ft}) + s_i\,SMB_t + h_i\,HML_t + e_{it}$

[4-factor model]: $R_{it} - R_{ft} = a_i + b_i\,(R_{mt} - R_{ft}) + s_i\,SMB_t + h_i\,HML_t + m_i\,UMD_t + e_{it}$

The reason for using two different normal return models was mainly to test for the robustness of results to specification errors in the normal return model.

The components of the models are as follows. Both models regress on the excess return of a stock i over and above the risk-free interest rate (on the left hand side of the equations). The rate on 30-days' Swedish Government bills was used to estimate the risk-free rate R_{ft}. To get the normal return R_{it} for one day, the risk-free daily rate per trading day was added back to the excess return estimated by the models. Both models include an intercept a_i. The first three explanatory variables are common to the models: from left to right, the market excess return (as in the CAPM model), a size factor SMB_t and a value/growth factor HML_t. The market return R_{mt} was approximated with the return on Affärsvärldens Generalindex, which is a broad value-weighted index of stocks listed on the Stockholm Stock Exchange.

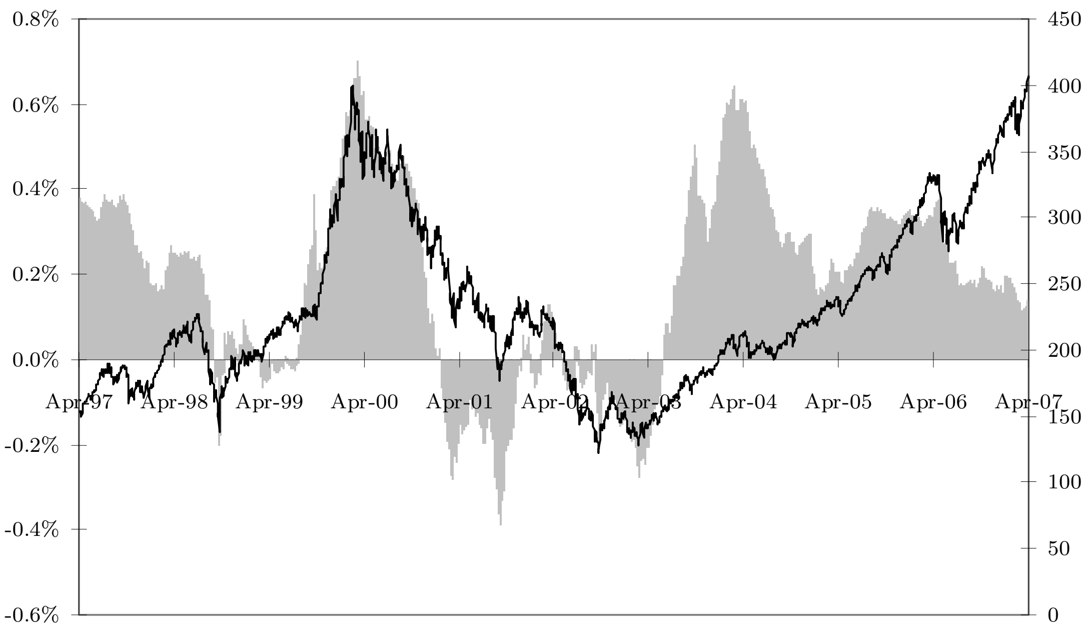
The 3-factor model was originally developed by Fama and French (1993), who used six portfolios formed from sorts of stocks on market value of equity (ME) and book-to-market equity, which is the ratio of book value of equity to market value of equity (BE/ME). The portfolios are intended as mimics of underlying risk factors in returns related to size and differences between growth stocks (low BE/ME) and value stocks (high BE/ME). Each month all stocks are ranked on ME. The median size is then used to split the stocks into two groups, small and big (S and B). Each month stocks are also ranked on BE/ME and three groups of stocks are formed based on the breakpoints for the bottom 30% (L), medium 40% (M) and top 30% (H) of the ranked values of BE/ME.

Six portfolios (SL, SM, SH, BL, BM, BH) are then created from the intersections of the two ME and the three BE/ME groups. Daily value-weighted returns on the six portfolios are calculated, and portfolios are reformed monthly. The size factor-mimicking portfolio SMB (small minus big), is calculated as the difference, each day, between the average return on the three small-stock portfolios (SL, SM and SH) and the average return on the three big-stock portfolios (BL, BM, and BH). The value/growth factor-mimicking portfolio HML (high minus low), is calculated as the difference, each day, between the average return on the two value-stock portfolios (SH and BH) and the average return on the two growth-stock portfolios (SL and BL).

The only difference between the two models is the fourth factor, which I added to filter out long-term price trends. The reason for adding this factor is that we want to isolate the effects of a particular earnings announcement from a longer market-wide trend in stock prices. Looking at Figure 3 below, it seems that long-term trends may indeed be an important feature in our sample. The average share in our sample has fallen into distinct positive trends during two periods, first from 1997 through to about 2000 (although a bit erratic) and from 2003 through to the end of the sample period. There is also a negative trend from about the beginning of 2000 to the end of 2003. For comparison, this conclusion seems valid also on a value-weighted basis by looking at the price graph of the value-weighted market index as shown in Figure 3. This evidence would support the notion that the 4-factor model is more appropriate to estimate normal returns. Following the method in Carhart (1997), each month stocks are sorted by return during the last year and portfolios are formed based on the breakpoints for the bottom 30% (*D*) and top 30% (*U*) of the ranked values. Daily equal-weighted returns on the two portfolios are calculated, and portfolios are reformed each month. The momentum factor-mimicking portfolio *UMD* (up minus down), is calculated as the difference, each day, between the average return on the portfolio of past one-year "winners" and "losers".

FIGURE 3 – SAMPLE PERIOD CHARACTERISTICS

1-year moving average of equally weighted daily returns (the shaded graph mapping onto the left axis), and as a comparison, the level of the value-weighted Affärsvärldens Generalindex (the black line mapping to the right axis).



For each stock on each announcement day, OLS regressions for both the 3-factor and the 4-factor model WERE run using 1 year of historical data for estimation. According to MacKinlay (1997), an appropriate length of this so-called estimation window is about 120 days, which I have taken as an indication of a minimum length. Using 1 year of data should give a more reliable estimation of coefficients. One could argue that the estimation window should ideally contain data for a full business cycle to give consistent results over time. However, there is also a trade-off between the length of the estimation window and the length of the period you have available for the study itself as you "lose" the length of the estimation window. By running new regressions for each observation I have allowed for the factor loadings to change dynamically, which intuitively should make the model both more accurate for periods of frequent changes in market price of various sources of risk and also average out over longer periods of time to give a fair estimation of long-run normal returns.

The estimated factor coefficients for each observation are then used throughout the so-called holding period (the period during which we take and hold positions in portfolios) to calculate abnormal returns under each of the two models. In other words, all stocks have different factor coefficients and they change for each earnings announcement, but they are kept constant throughout each earnings announcement period. Thus we have separate estimation windows and holding periods which do not overlap for an observation. To show how abnormal returns develop over time, we compute the returns for a number of different holding periods for each strategy.

3.3 Initial abnormal return (IAR)

As previously explained, initial abnormal return (IAR) was used to estimate the value of the new information released at an earnings announcement date (day 0). IAR is estimated as the abnormal return on the earnings announcement day. Abnormal return is estimated as the difference between the actual stock return for any given day (adjusted for dividends) and the estimated normal return as follows (using the 4-factor model as an example).

$$AR_{it} = R_{it} - (a_i + b_i\,(R_{mt} - R_{ft}) + s_i\,SMB_t + h_i\,HML_t + m_i\,UMD_t)$$

There are possible negative effects of using abnormal volume as the metric for portfolio formation compared to for example raw price changes. This is because the returns to the portfolios are also measured in abnormal return. If the normal return model was misspecified so that it systematically over- or underestimates abnormal returns, then the stocks in the extreme portfolios (the ones with the highest and lowest ranked IAR will also give the highest and lowest returns. However, using abnormal returns as the metric for portfolio formation will also, in my opinion, give the best estimate of the actual impact of the news. Since we recognize the difficulties that can arise, we can control for it. Besides, if the normal return model is misspecified we are better off knowing this than simply assuming it is correct. By calculating returns to all strategies using both a 3-factor and a 4-factor model, we can test the robustness of results to misspecifications in the model (although it will be difficult to say which of the two specifications is correct). I will come back to these robustness checks as I discuss the results later on.

3.4 Initial abnormal volume (IAV)

For abnormal trading volume, I have chosen to follow the example of Frazzini and Lamont (2006) and define this metric as follows. To approximate normal volume we use scaled volume (SV), defined as the share ratio of stock i today to average volume over the previous 21 trading days (one month).

$$SV_{i,t} = \frac{VOL_{i,t}}{\frac{1}{21}\sum_{s=21}^{1} VOL_{i,t-s}}$$

The reason for this scaling is that we want to measure how high the volume on an announcement day is relative to what is usual for the stock in question.

Initial abnormal volume (*IAV*) is defined as scaled volume minus the equal weight average across the whole sample of scaled volume on that day (denoting the number of stocks in the sample at time t by S):

$$IAV_{i,t} = SV_{i,t} - \frac{1}{S}\sum_{i=1}^{S} SV_{i,t}$$

By subtracting the average scaled volume for all stocks we adjust for market-wide surges in trading volume which is not caused by the information released at the earnings announcement.

3.5 Portfolio formation

This section explains how the portfolios are formed, which will then be used as the assets we use for our trading strategies.

For every quarter, portfolios are formed as follows:

1) *IAR* and *IAV* is calculated for the announcement day (day 0) for each observation

2) Quintile breakpoints are calculated using data from the preceding announcement period by ranking the *IAR* and *IAV* metrics and sorting the stocks (having rank 1 means having the highest metric, so for example the *IAR1* portfolio contains the stocks with the highest initial abnormal returns for that announcement period) A simple sorting of the stocks on each metric gives independent quintile breakpoints. Dependent quintile breakpoints are also calculated using a conditional double-sorting algorithm (i.e. conditional breakpoints for *IAV* given that a stock is placed within a given *IAR* quintile and vice versa). The benefit of dependent sorting is mainly that observations are distributed more evenly over the variable that is not dependent. The reason for using different algorithms for sorting the stocks is that we want to check

the robustness of results to the sorting methodology and could provide additional insights into how the two metrics are related.

The portfolio cutoffs are calculated using only previous data to avoid any so-called look-ahead bias in our results. To ensure that the strategies represent a trading scheme which is actually implementable, we cannot use breakpoints calculated with data from the current period of earnings announcements since not all stocks report at once and we will not be able to rank stocks without knowing IAR and IAV for all the stocks first. Instead, we resort to the next best thing: using data from the previous period of earnings announcements to calculate the breakpoints between portfolios and assuming that these breakpoints will divide up the stocks for the current period so that we get about an equal number of stocks in each quintile portfolio.

3) Using the breakpoints from 2) I sort the stocks into quintiles and form 5 portfolios based on IAR, 5 portfolios based on IAV, 25 portfolios based on the independent breakpoints for IAR and IAV, and 25 portfolios for each of the two sets of dependent quintile breakpoints. By independent double-sort we mean that we in principle plot each stock into a 5×5 matrix

Once the portfolios are created we can define a risk-neutral simple strategy by taking offsetting positions in any two portfolios. For example we could take a long position in the $IAR1$ portfolio, i.e. the stocks with the highest ranked (most positive) announcement day abnormal returns, and take an equally large short position in the $IAR5$ portfolio, i.e. the stocks with the lowest ranked (most negative) announcement day abnormal returns. The result will be that the returns to the strategy is isolated while the remaining risks such as market risk, size and book-to-market risk from our normal return models are cancelled out (at least for a sufficiently large number of stocks). Such a strategy would be self-financing (in theory) since the proceeds from the short trade could be used for the long trade. In practice there are transaction costs to take into account and some of the capital will be locked in margin requirements for the short trade.

3.6 Accumulation of abnormal returns

To determine the returns to the portfolios, we accumulate the abnormal returns for a given observation for the length of the desired holding period from τ_1 to τ_2 by simply adding abnormal returns (AR) so that we get a cumulative abnormal return (CAR).

$$CAR_{it}(\tau_1,\tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{it,\tau}$$

CARs for several holding periods are calculated to capture how the CAR develops over time. Specifically we have used an interval of 5 trading days (1 week) as follows: 1, 5, 10, 15, 20, 25 and so on up to 60 trading days, and we always use day 1, the day after the earnings announcement as our starting day. The reason for not looking at holding periods above 60 trading days is that shortly after that, another earnings announcement will take place with new information which could distort our results.

The next step is to accumulate the CARs from all the observations into an average CAR. Assuming that we have N observations throughout the entire 10-year period for a portfolio, then the average CAR is calculated as follows (where n is used as an index for all observations, summing over companies indexed by i and announcement periods indexed by t).

$$\overline{CAR}(\tau_1,\tau_2) = \frac{1}{N}\sum_{n=1}^{N} CAR_n(\tau_1,\tau_2)$$

To test if the average CARs for our portfolios are statistically significant we can use a t-test statistic as follows.

$$t = \frac{\overline{CAR}(\tau_1,\tau_2)}{\sqrt{\mathrm{var}(\overline{CAR}(\tau_1,\tau_2))}} \sim N(0,1)$$

The null hypothesis we are testing is whether the earnings announcement had an effect on abnormal returns (that the average CAR is not zero). According to MacKinlay (1997) the variance of a CAR_{it} is asymptotically (as the length of the estimation period increases) equal to the variance of the residuals from the normal return regression for multiplied by the length of the holding period.

$$\sigma_{it}^2(\tau_1, \tau_2) = (\tau_2 - \tau_1 + 1)\sigma_{\varepsilon_{it}}^2$$

This equation simply states that the variance of CAR will increase proportionally with the length of the holding period, i.e. variance will increase with the number of ARs we add to get the desired CAR. To get the variance of the average CAR for N observations that we need for our significance test, MacKinlay (1997) provides the following formula (where n indexes observations as previously explained).

$$\text{var}(\overline{CAR}(\tau_1, \tau_2)) = \frac{1}{N^2}\sum_{n=1}^{N}\sigma_n^2(\tau_1, \tau_2)$$

4 Empirical results and Analysis

This section presents the main findings of this thesis. First I will present and analyze the results to the individual *IAR* and *IAV* strategies together with some considerations for the robustness of results. Then I will move on to look at the results of a combined strategy using both independent and the dependent sorting algorithms. To keep this thesis as short as possible I will assume that the robustness checks apply to the combined strategies as well and not repeat them all over again (after all the combined strategies are only extensions of the simple strategies).

4.1 Abnormal returns to IAR strategies

Table 1 on page 26 shows the resulting average *CAR*s on an annualized basis for the five quintile *IAR* portfolios. The results to this strategy are presented both for the 3-factor and a 4-factor model as previously explained. The results vary considerably depending on which normal model is used. This does not necessarily mean that explained with the fact that the strategy itself is based on abnormal returns, so the portfolios will not contain the same stocks depending on which model you look at. Which model gives the most accurate results is of course debatable, but the presence of distinct long-term trends in the sample as would indicate that the 4-factor model could be more appropriate. Nevertheless, under the 3-factor model the strategy seems to not be able to generate any significant cumulative abnormal returns other than in the very short term after the earnings announcement. These results does not provide much indication of a momentum effect, and instead would support the notion that markets are indeed efficient when in terms of adjusting for both earnings- and non-earnings related information disclosed in conjunction with earnings announcements.

Under the 4-factor model on the other hand, the *IAR5* portfolio, i.e. “bad news firms” generates a significant annual negative abnormal return of 10.74% for a holding period of 45 trading days. A short position in that portfolio in combination with a long position in the corresponding *IAR1* portfolio would create a significant annualized abnormal return of 10.60%. In fact the long/short *IAR* strategy performs even better for a holding period of 40 trading days, creating an average annualized *CAR* of 11.25%. In general the abnormal returns to the strategy seem to be increasing with holding period and not become significant until after 30 holding days and above.

TABLE 1 – SIMPLE IAR STRATEGY

Average *CAR* in percent per annum and *t*-statistic for different holding periods for the five *IAR* portfolios (*IAR1* is the highest ranked quintile). Days are trading days. Spread is the difference between the *IAR1* and *IAR5* *CAR*s, equivalent to the return to a market risk-neutral long/short strategy. ** (*) represents significance at 1% (5%) level.

Note that any comparison of the results below must account for the portfolio formation technique used. Portfolios are formed based on abnormal returns (on the day of the earnings announcement). Hence, any particular quintile portfolio below will probably not contain the same stocks under a 3-factor model as under a 4-factor model. Therefore, while the results below can be used to draw inferences about how the strategy performs under different models, the results cannot be used to draw inferences about abnormal returns to any particular portfolio under different models.

3-factor model

Days	*IAR1*		*IAR2*		*IAR3*		*IAR4*		*IAR5*		*IAR* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
1	1.12*	2.57	.32	1.09	-1.12**	-3.38	-1.40**	-3.62	-1.91**	-3.28	3.03**	4.17
5	-.47	-.49	-.53	-.81	-2.72**	-3.67	-2.06*	-2.38	-3.41**	-2.62	2.94	1.80
10	-1.81	-1.31	-.74	-.80	-.39	-.37	-1.75	-1.43	-2.60	-1.41	.78	.34
15	-1.67	-.99	-.79	-.69	.69	.53	-.94	-.63	-.97	-.43	-.70	-.25
20	-2.78	-1.42	-1.49	-.76	.17	.09	-.90	-.46	.92	.47	-3.70	-1.90
25	-2.32	-1.06	-.18	-.13	.42	.26	-.88	-.46	.47	.16	-2.79	-.77
30	-3.15	-1.32	.42	.18	-.89	-.37	-2.21	-.93	-2.10	-.88	-1.05	-.44
35	-3.99	-1.55	-.03	-.02	-1.01	-.51	-3.84	-1.68	-3.95	-1.15	-.04	-.01
40	-4.31	-1.56	-.46	-.25	-.66	-.31	-4.89*	-2.00	-4.41	-1.20	.10	.02
45	-5.20	-1.78	.24	.12	.20	.09	-3.96	-1.53	-3.55	-.91	-1.64	-.34
50	-4.30	-1.39	.43	.21	-.64	-.27	-2.89	-1.06	-1.73	-.42	-2.57	-.50
55	-4.40	-1.36	-.01	.00	-.39	-.16	-2.38	-.83	-.94	-.22	-3.46	-.64
60	-4.14	-1.23	.14	.06	-.70	-.27	-2.10	-.70	-5.22	1.16	1.08	-1.66

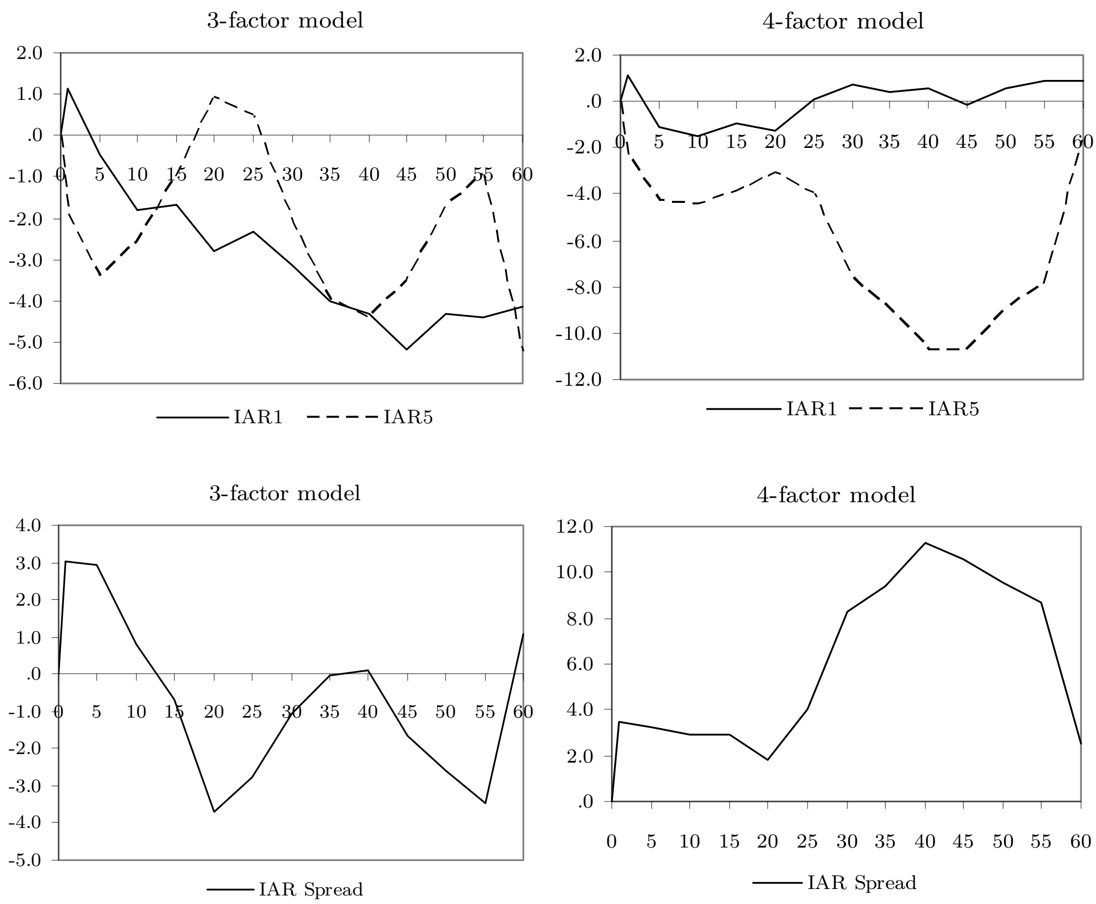
4-factor model

Days	*IAR1*		*IAR2*		*IAR3*		*IAR4*		*IAR5*		*IAR* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
1	1.09**	2.61	.32	1.10	-.99**	-3.03	-1.26**	-3.75	-2.37**	-4.94	3.47**	5.45
5	-1.12	-1.20	-.16	-.25	-3.03**	-4.14	-2.39**	-3.20	-4.32**	-4.02	3.20*	2.25
10	-1.53	-1.16	1.43	1.55	-2.22*	-2.14	-2.40*	-2.27	-4.45**	-2.93	2.92	1.45
15	-.96	-.59	1.85	1.63	-.77	-.60	-2.15	-1.66	-3.92*	-2.11	2.96	1.20
20	-1.28	-.69	1.86	1.00	-2.26	-1.21	-1.97	-1.05	-3.07	-1.64	1.79	.96
25	.09	.04	2.00	1.37	-1.71	-1.05	-1.97	-1.18	-3.95	-1.64	4.04	1.27
30	.70	.31	3.19	1.39	-3.10	-1.36	-3.41	-1.49	-7.62**	-3.33	8.32**	3.64
35	.38	.15	2.99	1.73	-2.63	-1.36	-4.98*	-2.52	-9.00**	-3.17	9.38*	2.49
40	.56	.21	2.65	1.43	-2.62	-1.27	-5.50**	-2.60	-10.69**	-3.52	11.25**	2.80
45	-.15	-.05	3.45	1.75	-2.61	-1.19	-3.54	-1.58	-10.74**	-3.33	10.60*	2.48
50	.61	.21	3.70	1.79	-2.81	-1.22	-2.83	-1.19	-8.98**	-2.64	9.59*	2.13
55	.85	.27	3.02	1.39	-2.13	-.88	-3.28	-1.32	-7.83*	-2.20	8.68	1.84
60	.90	.28	4.24	1.87	-2.09	-.82	-3.28	-1.27	-1.62	-.44	2.52	.51

FIGURE 4 – SIMPLE IAR STRATEGY

The left column of graphs shows the results using a 3-factor normal return model and the right column graphs show results using a 4-factor model to estimate normal returns. The upper graphs show abnormal returns in percent per year to the extreme portfolios of the individual *IAR* strategy. The bottom pair of graphs shows the spread to a long/short market neutral strategy.

Note that the results are not directly comparable between models as the stocks in the quintile portfolios changes as *IAR* changes.



As this strategy seems sensitive to the choice of normal return model I will perform some additional robustness checks. Looking at the graphs of CAR as a function of holding period in Figure 4, the differences form the two models become evident. The 3-factor model CARs and IAR spread fluctuates quite a bit, possibly indicating that there may be external factors not included in the model which affect the results. The 4-factor results on the other hand are more consistent in terms of the sign of the spread. Focusing our analysis on the 4-factor results since they show evidence of post-earnings announcement effects, we note that the strategy mainly benefits from negative returns on the bad-news portfolio while the good-news portfolio fluctuates around zero. The spread reaches a maximum at a holding period of 40 days and then quickly diminishes. One possible explanation for this abrupt change could be that the next quarterly report approaches (assuming 252 trading days per year gives 63 days for each quarter), prompting speculators using contrarian strategies to take positions and thus creating abnormal returns due to report-driven speculation.

Another possibility is that the factor loadings estimated in the normal return model have changed. The information in the earnings announcement could for example mean a significant change for the future business of the company and thus the stock's sensitivity to the risk factors in the model could have been altered. To investigate this I have re-estimated the factor loadings after 61 days. Statistics for the differences in the estimated coefficients are shown in Table 2 below. None of the changes in any of the coefficients or the intercept were found to be statistically significant and the mean changes are not unacceptably large and we always re-estimate the model for each new observation. This type of modeling problem should be more severe for studies with holding periods of a year or longer. In our case it seems safe to assume that the estimated coefficients using the 4-factor model on average are representative during the holding period and that the information released in the average earnings announcement does not have an unreasonably large impact on the risk profile of the stock.

TABLE 2 – CHANGES IN FACTOR LOADINGS

This table shows statistics of changes in the normal return model coefficients comparing estimation at day 0 (the announcement day) and at day 61. Changes should be normally distributed under the central limit theorem as the number of observations is large. Since we are interested in the magnitude of changes we will not use the *t*-statistic as positive and negative changes would cancel out on average. Instead we compute squared changes and use a chi-square test statistic under a null hypothesis of zero mean change. Root mean square of changes is also computed as an estimate of the average change magnitude. With 7,584 degrees of freedom the chi-square distribution requires a value of 7,873 to be significant at a 1% level and 7,788 at a 5% level.

4-factor model					
	a	b	s	h	m
Root of mean squared change	0.00368	0.256	0,145	0.203	0.174
χ^2	2,430	4,236	2,675	3,301	2,646

Turning back to the shortest holding periods in

Table 1, it is evident that a fairly large part of the *CAR*s is attributable to the abnormal return on the day immediately after the earnings announcement. One possible reason for this which could have implications for our conclusions on market efficiency is that earnings announcement on average take place late during the day so that the market has very limited time to process the new information and adjust prices on the same day. It could also be due to errors in the announcement dates. To test whether these considerations would have a substantial impact on the results, I have modified the *IAR* portfolio formation metric to include abnormal returns during a span of three days centered on the announcement day. I will refer to this modified metric as *IAR**. It corresponds to the *EAR* measure used by Brandt et al. (2006). Of course, with this measure, we have to push portfolio formation and holding periods forward one day, so results are not fully comparable with the original *IAR* strategy. The results are shown in Table 3 and Figure 5 below. A comparison to the results from the original *IAR* reveals distinct similarities in the shape of the spread curve and the fact that *CAR*s seem to change mainly after holding periods of 25-30 days. The *IAR** strategy is less profitable overall with few significant *CAR*s and negative spreads for shorter holding periods, but on the other hand it is more consistent for longer periods and does not drop as the next announcement approaches. This evidence supports our previous results as the post-earnings announcement effect seems to persist even as we use a portfolio formation metric which both leaves more room for the market to adjust prices and also allows for imprecision in the recorded announcement dates.

TABLE 3 – THREE-DAY IAR STRATEGY

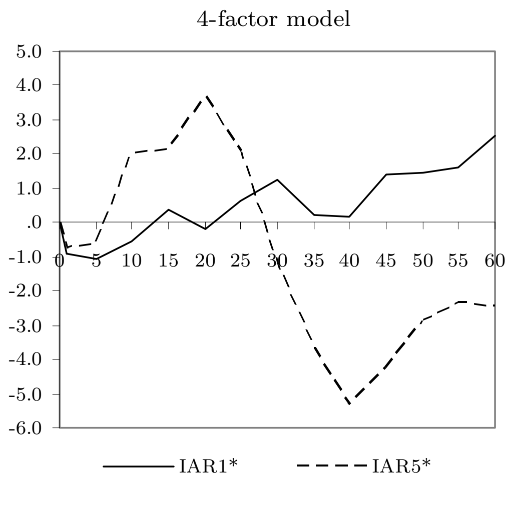
This table shows average *CAR* in percent per annum and *t*-statistic for different holding periods for the five quintile *IAR** portfolios (*IAR1** is the highest ranked quintile). *IAR** is a modified version of *IAR* measuring abnormal returns during a span of three days centered on the announcement day. Holding periods are shifted forward one day. These results are mainly used for checking the robustness of the original *IAR* strategy. Days are trading days. Spread is the difference between the *IAR1** and *IAR5** *CAR*s, equivalent to the return to a market risk-neutral long/short strategy. ** (*) represents significance at 1% (5%) level.

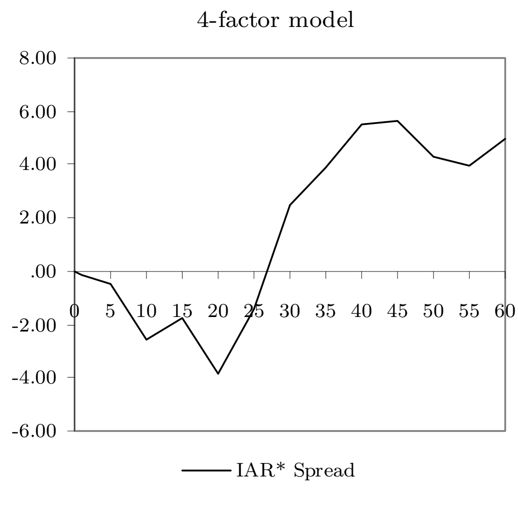
4-factor model

	*IAR1**		*IAR2**		*IAR3**		*IAR4**		*IAR5**		*IAR* Spread	
Days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
1	-.90*	-2.17	-.40	-1.28	-.97**	-3.33	-.46	-1.31	-.76	-1.57	-.15	-.23
5	-1.09	-1.17	-1.42*	-2.05	-2.70**	-4.17	-1.67*	-2.14	-.59	-.54	-.50	-.35
10	-.56	-.42	-2.25*	-2.30	-2.47**	-2.69	-1.76	-1.60	2.04	1.34	-2.59	-1.29
15	.39	.24	-.89	-.74	-1.49	-1.32	-2.39	-1.77	2.14	1.15	-1.75	-.71
20	-.20	-.11	-.68	-.37	-1.09	-.58	-3.37	-1.81	3.67*	1.97	-3.87*	-2.08
25	.63	.30	-1.19	-.77	-.97	-.67	-4.62**	-2.65	2.06	.85	-1.43	-.45
30	1.27	.56	-.11	-.05	-1.28	-.56	-5.26*	-2.31	-1.22	-.54	2.49	1.09
35	.23	.09	.12	.07	-1.89	-1.10	-6.18**	-3.00	-3.66	-1.28	3.89	1.03
40	.17	.07	.38	.19	-1.00	-.55	-6.60**	-2.99	-5.32	-1.74	5.49	1.36
45	1.38	.50	-.12	-.06	.04	.02	-6.60**	-2.82	-4.24	-1.31	5.63	1.32
50	1.44	.49	.31	.14	-.60	-.29	-5.54*	-2.25	-2.84	-.83	4.29	.95
55	1.60	.52	.25	.11	.03	.02	-5.33*	-2.06	-2.35	-.66	3.95	.84
60	2.52	.78	1.43	.60	.91	.40	.78	.29	-2.45	-.66	4.97	1.01

FIGURE 5 – THREE-DAY IAR STRATEGY

The left graph shows cumulative abnormal returns in percent per year to the extreme portfolios of the *IAR** strategy and the right graph shows the spread to a long/short market neutral strategy.





The results so far have not taken transaction costs into account. If the costs to exploiting the strategy exceeds its gains, then despite market inefficiency there is no post-earnings announcement anomaly in any practical sense. To investigate this, I look at transaction costs due to bid/ask spreads, because such costs would be unavoidable even to investors who are not restricted by paying trading commission (i.e. institutional investors such as hedge funds who could try to implement a strategy like this). I will assume that bid/ask spreads are small for large cap stocks and test if the strategy is still profitable when restricted to that subsample of stocks. I use market capitalization as the criteria because the Stockholm Stock Exchange has deprecated the old system (i.e. the A-list, O-list) in an effort to standardize listing procedures internationally (OMX Exchanges 2005). The results are presented in Table 4 and Figure 6 below and the distribution of observations over time is displayed in Table 8 in the Appendix. These results were quite unexpected. Not only are the post-earnings announcement effects still present, it turns out that they are much stronger for the large-cap subsample. The IAR strategy confined to large-cap stocks is superior in every respect to the same strategy on the full sample. In fact, the CARs are now significant for every single holding period. The highest CAR of 13.09% per year is earned for the longest holding period, and generally CARs increase with the length of the holding period. These abnormal returns are also likely subject to lesser transaction costs as previously explained. The CARs are attributable in about equal parts to the good-news portfolio and the bad-news portfolio. In essence, the results are very convincing to say the least, and weigh most heavily as evidence against the efficient market hypothesis.

TABLE 4 – LARGE-CAP IAR STRATEGY

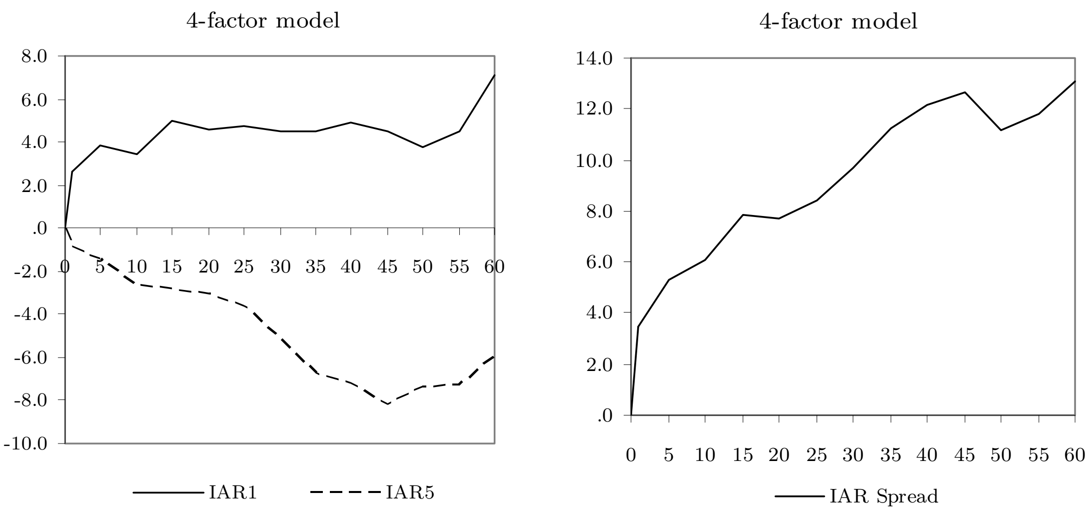
This table shows how the *IAR* strategy performs after restricting the sample to only large-cap stocks in order to check for robustness to transaction costs from bid/ask spreads. Average *CAR* in percent per annum and *t*-statistic for different holding periods for the five *IAR* portfolios (*IAR1* is the highest ranked quintile). Days are trading days. Spread is the difference between the *IAR1* and *IAR5 CAR*s, equivalent to the return to a market risk-neutral long/short strategy. ** (*) represents significance at 1% (5%) level.

4-factor model

	IAR1		*IAR2*		*IAR3*		*IAR4*		*IAR5*		*IAR* Spread	
Days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
1	2.60**	6.06	.25	.69	.60	1.68	-.30	-.85	-.87*	-2.19	3.46**	5.93
5	3.83**	4.00	.64	.77	.55	.70	-.43	-.55	-1.47	-1.66	5.30**	4.06
10	3.47*	2.56	1.26	1.08	-.35	-.31	-.25	-.22	-2.64*	-2.11	6.11**	3.31
15	5.03**	3.03	1.47	1.02	-.19	-.14	-.75	-.55	-2.83	-1.85	7.86**	3.48
20	4.62*	2.41	1.36	.71	-1.38	-.72	-1.55	-.81	-3.06	-1.60	7.68**	4.01
25	4.72*	2.21	1.70	.92	-1.72	-.97	-.49	-.28	-3.69	-1.86	8.41**	2.88
30	4.48*	2.33	.92**	-2.95	-1.90**	-2.70	-2.22	-1.45	-5.20	-1.45	9.68**	3.78
35	4.53	1.79	.58	.26	-2.31	-1.10	-2.33	-1.12	-6.72**	-2.87	11.25**	3.26
40	4.89	1.80	1.33	.57	-2.76	-1.23	-1.38	-.62	-7.26**	-2.90	12.15**	3.29
45	4.49	1.56	.53	.21	-3.78	-1.59	-.39	-.17	-8.19**	-3.09	12.68**	3.24
50	3.77	1.24	1.53	.58	-4.88	-1.95	-.65	-.26	-7.43**	-2.65	11.20**	2.71
55	4.53	1.43	1.22	.44	-5.61*	-2.14	-.86	-.33	-7.30*	-2.49	11.83**	2.74
60	7.07*	2.13	.64	.22	-6.09*	-2.22	-.32	-.12	-6.03*	-1.97	13.09**	2.90

FIGURE 6 - LARGE-CAP IAR STRATEGY

The left graph shows cumulative abnormal returns in percent per year to the extreme portfolios of the *IAR* portfolios in large-cap stocks only and the right graph shows the spread to a long/short market neutral strategy.



4.2 Abnormal returns to the IAV strategies

The results to the initial abnormal volume strategy are presented in Table 5 and Figure 7 below. As for the *IAR* strategy, the results are shown both for a 3-factor model and a 4-factor model. For this strategy portfolios are not formed based on abnormal returns so the results are comparable across both portfolios as well as estimation models. For the *IAV* strategy, results are more similar in terms of return patterns between estimation models although the 4-factor model still yields the most significant abnormal returns. This could be an indication that the choice of normal return model in fact does not change the basic patterns of abnormal returns as much as the model comparison for the *IAR* strategy would suggest. Instead it seems that it may be the portfolio formation breakpoints which are very sensitive to small changes in abnormal returns. One possible explanation could be that we calculate "best guess" quintile breakpoints using data from the previous announcement period, and thus have no guarantee that the number of stocks in each portfolio will be about 1/5 of the total for each period. However, judging from Table 7 in the Appendix, the differences in the number of stocks in each quintile portfolio are almost negligible.

In contrast to the *IAR* strategy it is the highest ranked portfolios which generate the highest abnormal returns for the *IAV* strategy. For example the *IAV1* portfolio yields a significant average *CAR* of 5.72% for a holding period of 25 days for the 3-factor model and almost as much for the 4-factor model, 5.04% to be precise. Although hardly any of the *IAV5* portfolio *CAR*s are significant the returns from a long/short strategy is more balanced here compared to the *IAR* strategy. For the 3-factor model, the largest significant average annualized cumulative abnormal return is 4.72% per year for a holding period of 30 trading days after the earnings announcement. Under a 4-factor model significant abnormal returns of up to 8.16% can be earned for a holding period of 40 days. Compared to the results from the *IAR* strategy, the returns do not fluctuate as much for different holding periods. Overall, the evidence for an momentum effect pertaining to a strategy based on abnormal volume seem more convincing than for a momentum effect for an abnormal returns-based strategy.

TABLE 5 – SIMPLE IAV STRATEGY

Average *CAR* in percent per annum and *t*-statistic for different holding periods for the five *IAV* portfolios (*IAV1* is the highest ranked quintile). Days are trading days. Spread is the difference between the *IAV1* and *IAV5* *CAR*s, equivalent to the return to a market risk-neutral long/short strategy. ** (*) represents significance at 1% (5%) level.

Note that as portfolios are formed independently of abnormal returns (on the day of the earnings announcement), the results below can be used to compare both how the strategy performs under different models, as well as how the abnormal returns to any particular portfolio changes under different models.

3-factor model

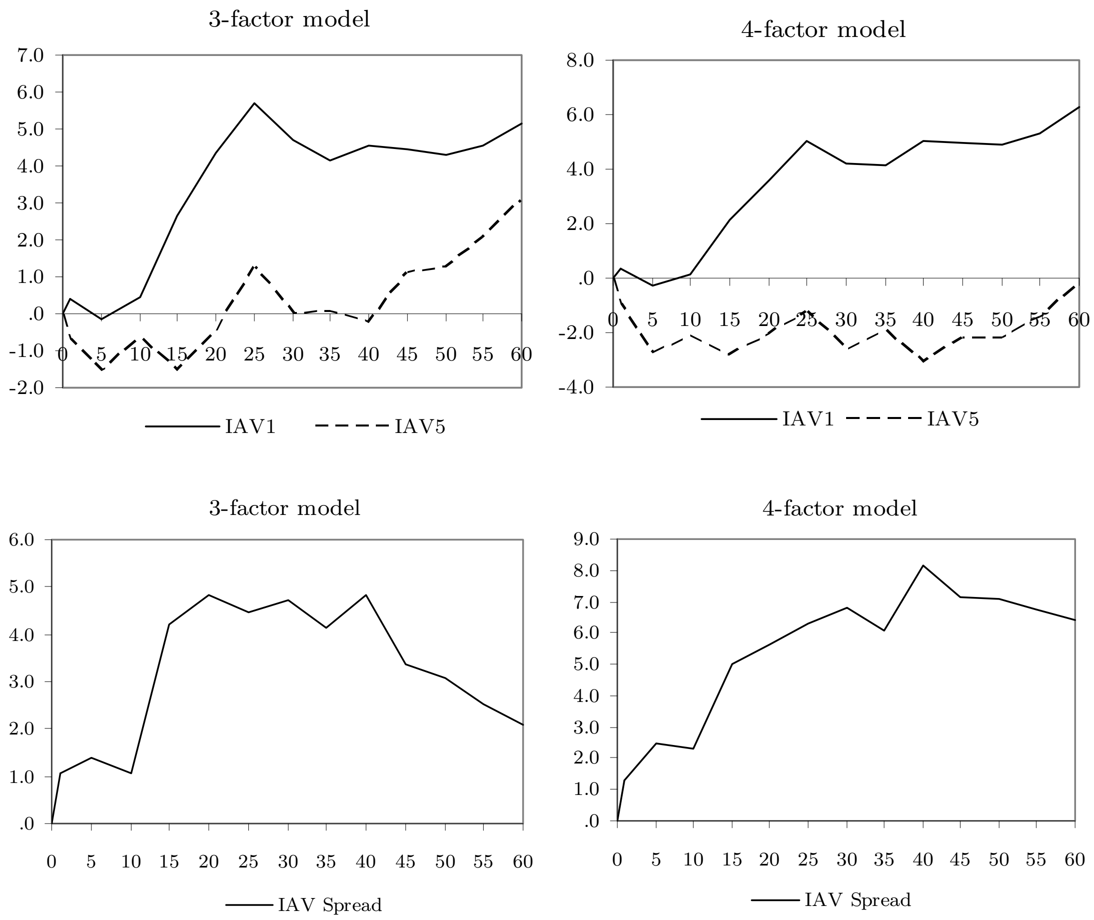
	IAV1		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
Days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
1	.38	1.13	-1.17**	-3.39	-1.05**	-2.88	-.62	-1.56	-.68	-1.11	1.06	1.51
5	-.17	-.22	-1.62*	-2.10	-2.85**	-3.50	-3.32**	-3.75	-1.54	-1.12	1.38	.88
10	.43	.40	-2.21*	-2.02	-2.84*	-2.47	-2.36	-1.88	-.63	-.32	1.06	.48
15	2.65*	2.04	-2.18	-1.63	-1.74	-1.23	-1.28	-.84	-1.56	-.65	4.21	1.55
20	4.33**	2.88	-2.63	-1.70	-2.85	-1.75	-2.83	-1.60	-.52	-.19	4.84	1.54
25	5.72**	3.40	-3.64*	-2.11	-3.61*	-1.98	-2.81	-1.42	1.25	.41	4.47	1.27
30	4.72*	2.57	-5.13**	-2.79	-4.49*	-2.44	-3.73*	-2.03	.00	.00	4.72*	2.57
35	4.17*	2.10	-6.29**	-3.08	-6.19**	-2.87	-5.43*	-2.32	.04	.01	4.13	.99
40	4.57*	2.15	-6.39**	-2.93	-7.00**	-3.04	-6.51**	-2.60	-.25	-.06	4.81	1.08
45	4.47*	1.98	-7.19**	-3.10	-6.24*	-2.56	-5.20	-1.96	1.09	.26	3.37	.72
50	4.30	1.39	-6.68**	-3.21	-4.42	-1.89	-4.21	-1.54	1.24	.30	3.06	.60
55	4.56	1.83	-6.14*	-2.40	-4.10	-1.52	-5.04	-1.72	2.05	.45	2.51	.48
60	5.17	1.53	-5.91**	-2.59	1.52	.59	-5.43	-1.81	3.07	.68	2.10	.37

4-factor model

	IAV1		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
Days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
1	.33	1.01	-1.16**	-3.43	-.93**	-2.60	-.68	-1.75	-.97*	-2.05	1.30*	2.25
5	-.30	-.41	-1.69*	-2.24	-2.99**	-3.75	-3.50**	-4.06	-2.77**	-2.61	2.47	1.91
10	.16	.15	-2.34*	-2.18	-2.94**	-2.61	-2.22	-1.82	-2.14	-1.43	2.30	1.26
15	2.17	1.70	-2.57*	-1.96	-2.12	-1.53	-1.06	-.71	-2.85	-1.55	5.02*	2.25
20	3.56*	2.42	-2.94	-1.94	-3.23*	-2.03	-2.59	-1.50	-2.06	-.97	5.62*	2.18
25	5.04**	3.06	-4.10*	-2.42	-3.95*	-2.21	-2.08	-1.08	-1.26	-.53	6.30*	2.18
30	4.20*	2.33	-5.32**	-2.95	-4.87**	-2.70	-2.61	-1.45	-2.62	-1.45	6.82**	3.78
35	4.15*	2.13	-6.20**	-3.09	-6.36**	-3.02	-3.98	-1.75	-1.92	-.68	6.07	1.78
40	5.05*	2.42	-5.86**	-2.74	-7.40**	-3.28	-5.53*	-2.27	-3.11	-1.04	8.16*	2.23
45	4.93*	2.23	-6.58**	-2.90	-6.72**	-2.81	-4.31	-1.67	-2.20	-.69	7.13	1.84
50	4.87	1.65	-5.15*	-2.49	-5.16*	-2.23	-3.76	-1.59	-2.19	-.65	7.07	1.57
55	5.29*	2.17	-4.46	-1.78	-4.98	-1.88	-4.79	-1.68	-1.44	-.41	6.73	1.57
60	6.26	1.93	-3.91	-1.72	.58	.23	-5.03	-1.94	-.18	-.05	6.43	1.31

FIGURE 7 - SIMPLE IAV STRATEGY

The left column of graphs shows the results using a 3-factor normal return model and the right column graphs show results using a 4-factor model to estimate normal returns. The upper graphs show abnormal returns in percent per year to the extreme portfolios of the individual *IAV* strategy. The bottom pair of graphs shows the spread to a long/short market neutral strategy.



To see if the results will persist when transaction costs are low, we restrict the sample to large-cap stocks like we did previously for the *IAR* strategy. The results are shown in Table 6 and Figure 8 - Large-Cap *IAV* strategy on the next page.

The results are in line with previous findings for the full-sample basic strategy. The *CAR*-patterns are similar with the portfolio with the most positive abnormal volume *IAV1* creating the largest part of the spread while the most negative abnormal volume portfolio *IAV5* relatively unchanged. Very few of the *CAR*s are significant. The spread is also less consistent and smaller in magnitude, which would indicate that this strategy is indeed sensitive to transaction costs. The overall impression is that the abnormal volume strategy still seems viable after taking transaction costs into account, but the returns are clearly eroded compared to the full sample returns. This lends some support to the efficient market hypothesis as at least a portion of the post-earnings announcement effects previously found could be explained as a risk premium to low-liquidity stocks.

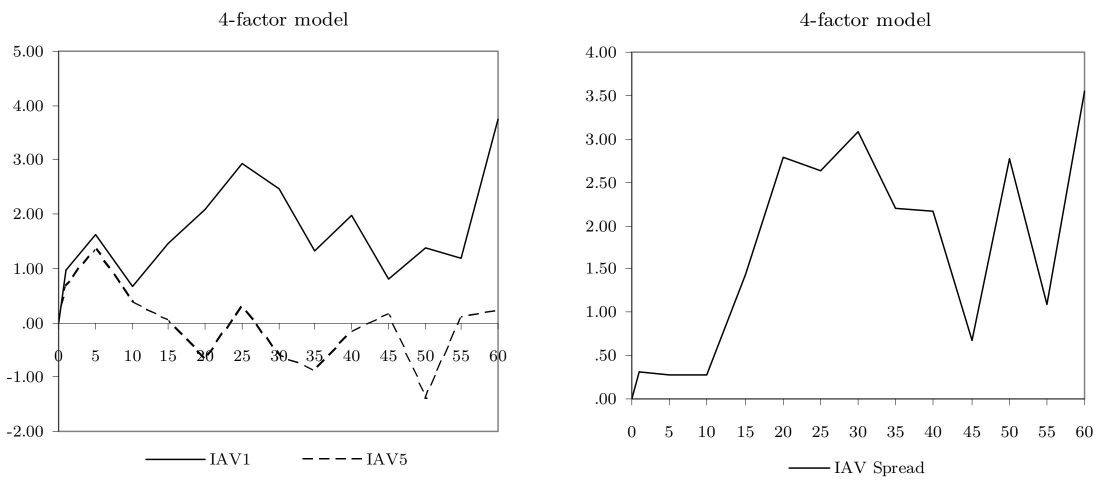
TABLE 6 – LARGE-CAP IAV STRATEGY

This table shows how the *IAV* strategy performs after restricting the sample to only large-cap stocks in order to check for robustness to transaction costs from bid/ask spreads. Average *CAR* in percent per annum and *t*-statistic for different holding periods for the five *IAV* portfolios (*IAV1* is the highest ranked quintile). Days are trading days. Spread is the difference between the *IAV1* and *IAV5* *CAR*s, equivalent to the return to a risk-neutral long/short strategy. ** (*) represents significance at 1% (5%) level.

4-factor model												
	IAV1		*IAV2*		*IAV3*		*IAV4*		*IAV7*		Spread	
Days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
1	.97*	2.42	-.10	-.25	.73*	2.00	-.21	-.55	.66	1.76	.31	.56
5	1.63	1.82	-1.36	-1.60	1.85*	2.26	-.75	-.88	1.36	1.62	.27	.22
10	.66	.52	-1.95	-1.62	2.57*	2.22	-.52	-.43	.38	.32	.28	.16
15	1.46	.94	-1.30	-.88	2.97*	2.10	-.90	-.60	.03	.02	1.43	.67
20	2.10	1.17	-2.84	-1.67	2.43	1.48	-1.44	-.84	-.69	-.41	2.78	1.13
25	2.93	1.46	-3.35	-1.76	1.46	.80	-1.28	-.67	.30	.16	2.63	.96
30	2.47	1.12	-4.33*	-1.97	.99	.45	-3.10	-1.41	-.62	-.28	3.08	1.40
35	1.32	.55	-4.10	-1.82	-.04	-.02	-3.25	-1.44	-.87	-.39	2.19	.67
40	1.97	.78	-4.77*	-1.98	-.03	-.01	-2.90	-1.20	-.18	-.08	2.16	.62
45	.81	.30	-4.99	-1.95	-.58	-.23	-3.46	-1.35	.14	.06	.67	.18
50	1.38	.45	-4.71	-1.80	-.88	-.35	-2.56	-1.03	-1.39	-.50	2.77	.67
55	1.19	.40	-5.72*	-2.02	-1.33	-.49	-2.82	-1.00	.09	.03	1.10	.27
60	3.76	1.13	-6.12*	-2.13	.05	.02	-3.21	-1.18	.21	.07	3.55	.79

FIGURE 8 - LARGE-CAP IAV STRATEGY

The left graph shows cumulative abnormal returns in percent per year to the extreme *IAV* portfolios in large-cap stocks only and the right graph shows the spread to a long/short market neutral strategy.



4.3 Abnormal returns to combined IAR/IAV strategies

The results for the individual strategies give us some encouragement to go ahead and investigate how a combined strategy would perform. The results to such a strategy are displayed in Table 7Table 7 in the Appendix. Here I have restricted the presented results to how this strategy would perform under a 4-factor model since that proved to give the most compelling results for the individual IAR strategy. If the IAR and IAV strategies are independent earnings announcements effects, then we should be able to create even higher abnormal returns from a combined strategy compared to the individual strategies taken separately.

From the related research we have reviewed previously we have learned that momentum effects (i.e. underreaction) is what we would normally expect when looking at earnings information such as the SUE metric and thus it would seem likely that any effect found for non-earnings related information would be of the same nature. If that was indeed the case then we would expect to earn larger abnormal returns than for the individual strategies by taking long/short positions in the portfolios that are found on opposite ends of the top-left to bottom-right diagonal for any given holding period, and so take advantage of both strategies simultaneously. Looking at the scatterplots in Figure 11 in the Appendix there are no obvious signs of correlation between the two strategies, which would suggest that they are independent.

However, as we can see from the results presented in Figure 9, Figure 10 and Table 11 in the Appendix this does not seem to be the case. For example, the lower-right portfolios in Table 11 actually generate positive abnormal returns for holding periods of 1, 10 and 20 days. Using the 20-trading days holding period as an example, it seems that the lower-right portfolio which is in the $IAR5$ quintile (and thus had the most negative reactions on the day of the earnings announcement) experiences a reversal effect since it generates an average abnormal return of about 4.09% per year. The $IAR5IAV4$ portfolio just to the left displays a substantial (although not significant) average negative abnormal cumulative return of about 9.34% per year. This shows that the IAR strategy does not perform consistently across the IAV strategy. The IAV strategy, on the other hand does indeed produce a monotonously increasing spread across the IAR quintiles for these holding periods.

For the longer holding periods of 40 days and 60 days on the other hand, the combined strategy seems to work as we had anticipated and indeed creates a spread of 11.95% and 5.71% respectively. The most profitable and consistent strategy is the *IAV* strategy in the good-news portfolio, which generates an abnormal return of 13.0% for 55 holding days, which is about equally based on a momentum for high-volume stocks (4.01%) and a reversal for low-volume stocks (8.98%). However, looking in Table 11 there are hardly any significant abnormal returns to speak of and the general impression must be that a combined strategy using independent sorting would not create any additional abnormal returns compared to the individual strategies.

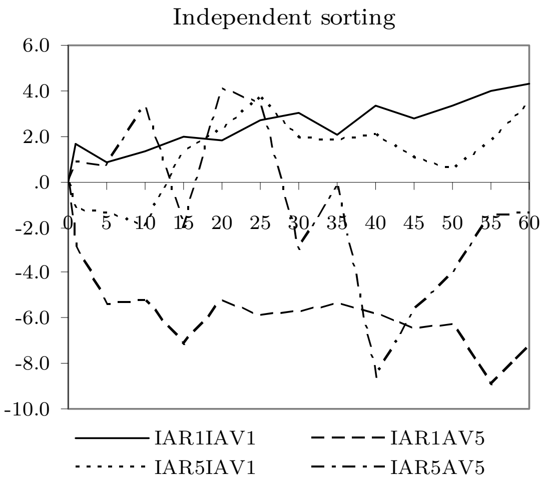
Looking at the results for the *IAR*-dependent sorting in Figure 9, Figure 10, and Table 12 in the Appendix, we begin to look at how the *IAV* strategy performs within the *IAR* strategy. The most striking thing is the large positive *CAR*s of 17.04% in the bad-news/high-volume portfolio (*IAR5IAV1*) for a 60-day holding period. Thus there is a large reversal effect. Combined with a momentum of 6.47% in the bad-news/low-volume portfolio the *IAV* strategy within the "bad news" portfolio (*IAR5*) results in a positive spread of 23.5%. The *IAR* strategy performs correspondingly poor within the high-volume portfolio, punished by the short position in the reversing *IAR5IAV1* portfolio previously mentioned and yields a negative return of 14.95% for 60 days holding period. The combined strategy (the "diagonal" spread) performs quite well, yielding a total abnormal return of 8.56% of which 2.08% comes from a long position capitalizing on a momentum effect in the good-news/high-volume portfolio and 6.47% from a short position from momentum in the bad-news/low-volume portfolio. Despite seemingly large magnitudes, the relatively low number of statistically significant results reduces the value of these results as evidence for post-announcement earnings affects.

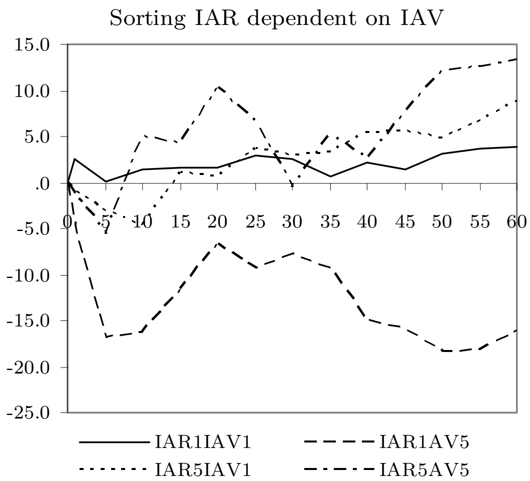
When looking at the results for the *IAV*-dependent sorting, we begin to look at how the *IAR* strategy performs within the *IAV* strategy. Figure 9, Figure 10 and Table 13 in the Appendix indicates that the largest *CAR*s seem to be created for the portfolios with the lowest abnormal volume, but the signs are reversed. The most striking feature is that the magnitude of the effect is very large, creating a negative spread of 30.81% for a holding period of 55 days. It is due to reversals in both the long and the shorted portfolio in about equal parts, which is why we get a negative sign when taking the usual long/short positions. The *IAV* strategy on the other hand performs well within the *IAR* strategy, creating a positive spread of 21.60% for the quintile portfolio with the highest abnormal returns for the 50 days period. This effect is mainly due to reversal in low-abnormal volume stocks. The combined strategy is dominated by the reversal effect in the bad-news/low-volume portfolio ($IAR5IAV5$) and thus produces a negative return of 9.50%. Overall, despite these high spreads, there are few significant CARs, which would indicate that the variance within portfolios is high and thus the results may be less trustworthy.

FIGURE 9 – COMBINED PORTFOLIO RETURNS

The graphs show cumulative abnormal returns to the four extreme portfolios (in the corners of the *IAR*/ *IAV* matrix) of each sorting algorithm. All abnormal returns are in percent on an annualized basis.

4-factor model





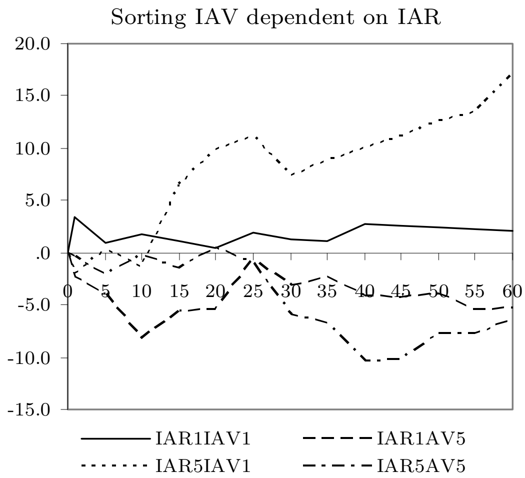


FIGURE 10 –COMBINED STRATEGY SPREADS

Each set of 3 graphs below shows the spread to different long/short market neutral strategies. The first is the combined (diagonal left-to-right) spread, the second are the two (horizontal) *IAV* spreads given *IAR* and the third are the two (vertical) *IAR* spreads given *IAV*. All abnormal returns are in percent on an annualized basis.

4-factor model, independent sorting

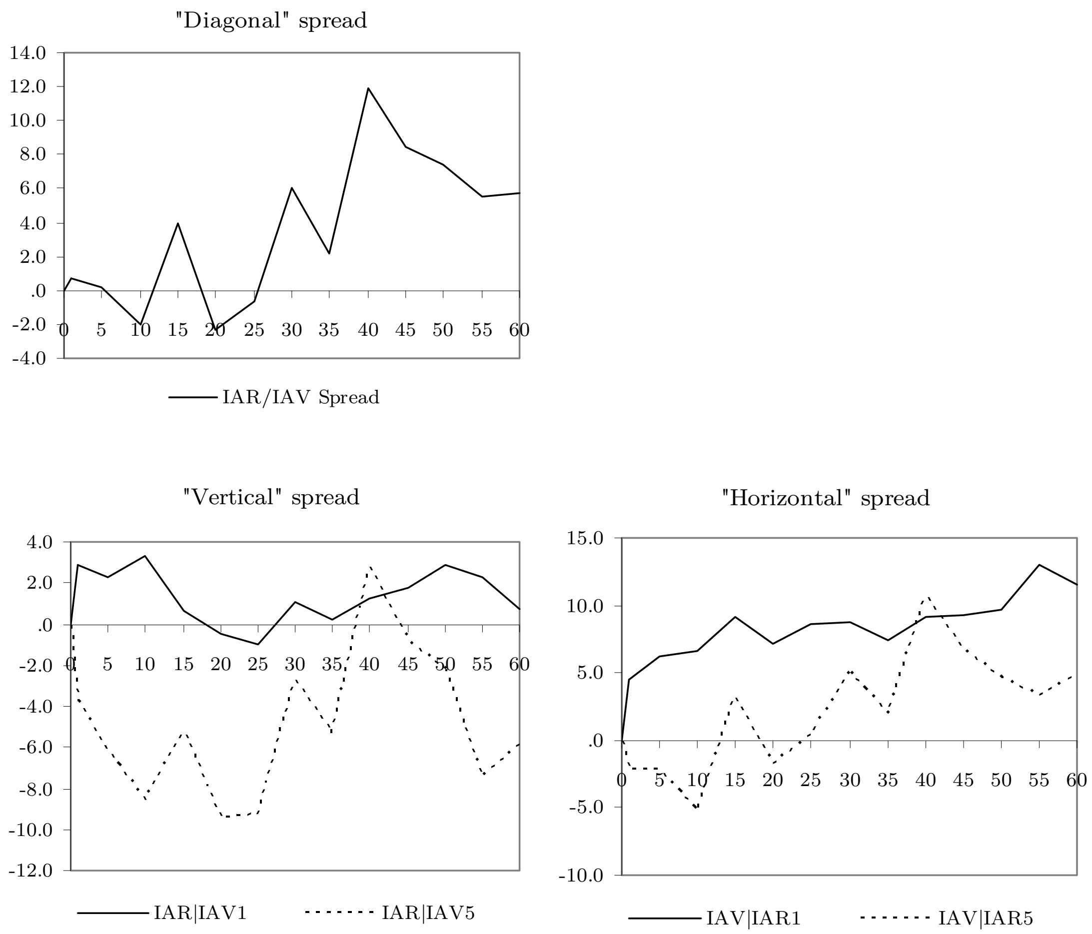
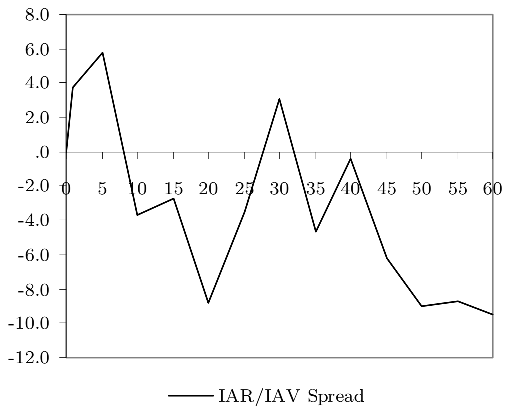


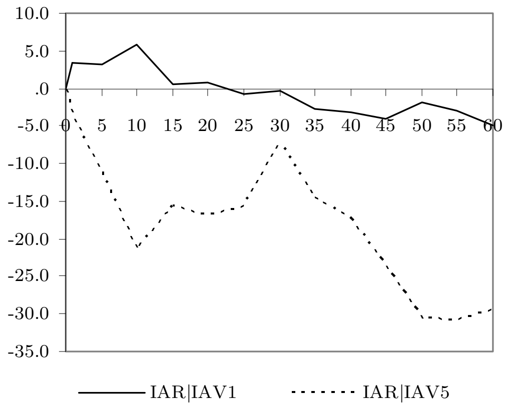
FIGURE 10 (CONT.)

4-factor model, sorting *IAR* dependent on *IAV*

"Diagonal" spread



"Vertical" spread



"Horizontal" spread

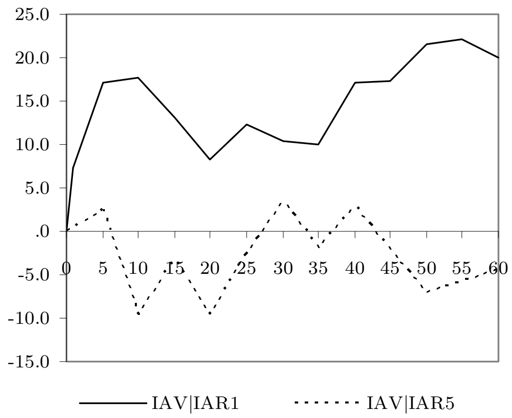
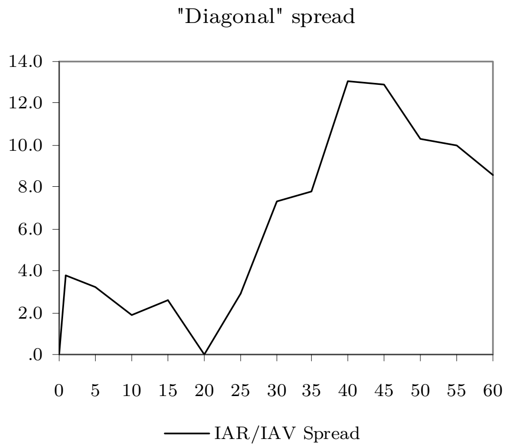
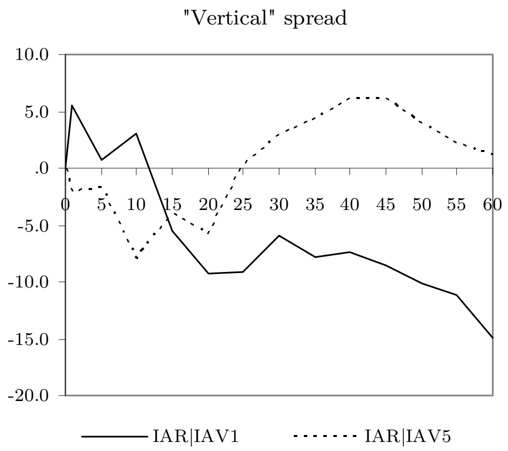
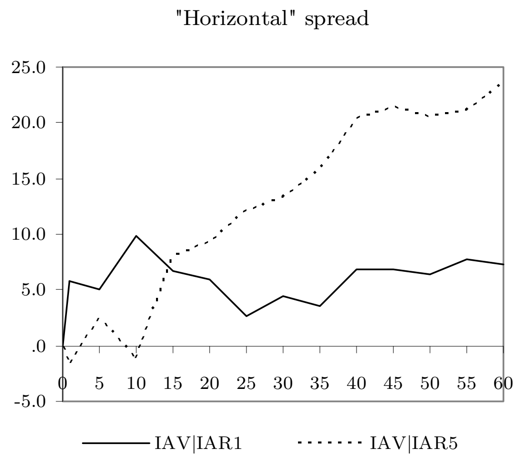


FIGURE 10 (CONT.)

4-factor model, sorting *IAV* dependent on *IAR*







5 Conclusion

In this thesis I investigate the presence of post-earnings announcement effects on the Swedish stock market over the decade ranging from 1997 to 2007 and how this phenomenon is related to the nature of information released at the earnings announcement. Abnormal changes in price (*IAR*) and abnormal changes in volume (*IAV*) are considered as proxies for the value of both earnings- as well as non-earnings information released in press-releases and press-conferences, and amount/complexity of this information. A large dataset was used consisting of data for 272 stocks and a total of over 8,000 observations of earnings announcements. Two different models were used to estimate abnormal returns, both a Fama-French 3-factor model and an extended trend-correcting 4-factor model adding another factor to account for long-term trends. The method employed was portfolio formation based on two different metrics, both individually into 5 quintile portfolios and combined into 25 portfolios. Both independent and dependent sorting was used to form quintile breakpoints. The strategies used were straightforward: take long/short positions in the extreme portfolios (long in high metrics and short in low metrics) to create a market neutral portfolio.

Evidence of a post-earnings announcement effect (momentum) was found for the abnormal volume metric which suggests that markets are not efficient. However, the evidence does not seem to be robust enough to warrant a rejection of the efficient market hypothesis. Nevertheless, a long position in the highest quintile portfolio of initial abnormal volume (*IAV1*) combined with a short position in the lowest quintile (*IAV5*) earned a significant abnormal return of ranging from 4.72% to 8.16% per year depending on normal return model used and holding period. The results were consistent independent of which normal return model was used. However, restricting the sample to only large-cap stocks made the strategy a bit less profitable but still earning abnormal returns of 3.55% for the 60-day holding period. This leads to the conclusion that transaction costs should not be preventing investors from exploiting this anomaly.

Evidence of a momentum effect for initial abnormal return was found, although a bit weaker, mainly because the results differed greatly depending on the choice of normal return model. However, for a 4-factor model, significant abnormal returns to a long/short strategy in the extreme portfolios (*IAR1* and *IAR5* respectively) were found ranging from 8.32% to a very respectable 11.25% per year depending on the holding period. Generally, the longer holding periods of above 40 trading days seem to be able to generate higher abnormal returns than shorter holding periods. When restricting the sample to large-cap stocks, the evidence for a momentum effect was much stronger, gaining a highly significant 13.09% abnormal return for the longest holding period of 60 days. The 4-factor model results were persistent even using an extended abnormal return metric for three days centered on the announcement day instead of only the announcement day. The reason for this robustness check was to leave more room for the market to adjust prices and also allow for imprecision in the recorded announcement dates. The conclusion is that for the 4-factor model there is very compelling evidence for post-earnings announcement effects, which would contradict the efficient market hypothesis. For a 3-factor model, the evidence seems to point towards market efficiency. The question of which risk-adjusted return model is the most accurate has been subject to much debate and falls outside the scope of this thesis. Nevertheless, long-term trends in prices seem to be a distinct feature of the sample period, which would support the use of the 4-factor model, and thus the evidence against market efficiency would weigh somewhat heavier.

Little evidence was found to support a joint strategy of the two metrics when using an independent sorting to form portfolio. The combined ("diagonal") strategy yielded only 5.71% for 60 holding days, which is no great improvement over the individual strategies. However, the IAV strategy seems to perform better for good-news firms, achieving abnormal returns of up to 13%. When using dependent double sorting on volume, this figure is upped to as high as 22.05% for a holding period of 55 days. Interestingly, when using this sorting algorithm, the IAR strategy for the low-volume portfolio also creates a negative abnormal return of 30.81% for the 55 day holding period. This result arises due to post-announcement reversals for both the good-news portfolio (-18.28%) and the bad-news portfolio (+12.53%). As an effect of this reversal, the combined ("diagonal") strategy also generates highly negative abnormal returns (-9.50% for 60 days holding period). When instead using dependent double sorting on abnormal return, the IAV strategy on the bad-news portfolio produced abnormal returns of 23.52%, due to reversal for the bad-news/high-volume portfolio (+17.04% for 60 days) and a momentum for the bad-news/low volume portfolio (-6,47%).

Although these mixed results do not lead to any clear conclusion about reversal and momentum patterns, it is still an interesting result showing that the strategies are only partially independent of each other and quite sensitive to which sorting algorithm is used. This is after all not so surprising since previous research have found abnormal returns and trading volume to be correlated (Karpoff 1987). To estimate how these results relate to what I expected beforehand as illustrated in Figure 1 on page 14, I have compared the expected and the actual signs of the abnormal return of the four extreme portfolios (the corners in the combined portfolios matrix), summing over all three sorting schemes and all 13 holding periods. It seems that my expectations were 100% correct for both the good-news/high-volume portfolio (the upper-left square in Figure 1) and for the good-news/low-volume portfolio (the upper-right square). For the bad-news/high-volume portfolio (the lower-left square) the prediction was correct only 18% of the times and for the bad-news/low-volume portfolio (the lower-right square) the prediction was right 61% of times.

The implication of this unexpected reversal pattern observed for the bad-news/high-volume portfolio would be that some stockowners initially interpret the information as more negative than it actually is, and so they hurry to sell the stock only to see it rebound over the next 60 days. This seems counterintuitive to my assumption that the owners of a stock know their company better than the average non-owner. Such basic logic is hard to argue against, so in order to find an explanation we need to make it more complex first. We can for example add an assumption that the owners selling on an announcement day are not representative in the sense that they are more speculative than owners selling on any other given day – i.e. they have not bothered to learn anything about the company, they are just interested in the stock price in the short-term. Then, one possible alternative explanation for the observed reversal pattern could be that the initial reaction is more like a measure of the difference between what speculators had expected the company to report and what it actually reported (more like the *SUE* measure). Then we would see initial negative abnormal returns even though the news was essentially good news, followed by a reversal when the speculators moved on elsewhere. Whether this explanation holds any truth I will leave for other studies to investigate.

The findings in this thesis agree quite well with previous research findings, for example in comparison with the abnormal returns found by Bernard and Thomas (1989), Brandt et al (2006) and Frazzini and Lamont (2006) (although keeping in mind that their strategies were different in several respects). To the extent that some of my results are quite large in magnitude, those results tend to involve a rather elaborate trading scheme (e.g. earning 30.81% per year using the *IAR* strategy on the *IAV5* portfolio with dependent double-sorting on *IAV* and holding for 55 days). One surprising find was that the simple *IAR* strategy performs so much better on the large-cap subsample than on the full sample, earning a whopping abnormal return of 13.09% per year the 60 days holding period. I have no good explanation for why this is the case since I have corrected for size and book/value effects in the normal return model. Nevertheless, the relatively large abnormal returns compared to other recent studies from the US market cited earlier are not that surprising since I expected the Swedish market to be comparatively less efficient. On the other hand, some of my results show magnitudes much smaller than what other researchers have found. For example Foster, Olsen and Shevlin (1984) found evidence of annualized abnormal returns as high as 25% to a relatively simple strategy. One possible reason for finding smaller abnormal returns now than in previous studies could be that the effect has been shown to decrease over time since it was first discovered, (see e.g. Johnson and Swartz Jr. (2000) for a discussion of this phenomenon.).

The results found seem economically significant even after correcting for transaction costs, especially the *IAR* strategy. I believe the abnormal returns would most likely be enough to exceed transaction costs and could therefore be considered viable investment schemes for many investors, especially institutional investors who face lower transaction costs than for example private investors. One problem could of course be short-selling constraints, especially in the case of the strategies whose returns are skewed towards the negative side and therefore must rely on the short position to generate the bulk of abnormal returns. I have not investigated in any detail the availability of stocks for shorting deals. Restricting the universe to large-cap stocks would probably increase the availability, so the results for the large-cap subsample should be more reliable in that respect.

In terms of reliability of results, I have performed a number of tests to measure the robustness in results to various assumptions and choices in methodology. I have also tried to minimize various kinds of errors and improve accuracy of results, for example by checking the correctness of earnings announcement dates by comparing records from several sources. I have not removed any data other than obviously erroneous earnings announcement dates. Neither have I restricted the sample selection in unnecessary ways, such as only considering large-caps stocks. The number of companies in the sample is thus quite large, indicating that it should be representative of the entire population and thus that results should be general and trustworthy. The time period of 10 years is also relatively long, including both upturns and downturns on the stock market, and it should also be sufficiently long to contain at the very least one full business cycle. The method used in this thesis has its roots on the event study methodology which is well established and it should therefore be possible for anyone to replicate this study. In conclusion, I can think of no major source of error or bias that could compromise the reliability of results, which I have not tried to minimize as best I could.

6 Appendix

TABLE 7 – SIMPLE IAR PORTFOLIOS

Distribution of observation over time for the quintile IAR portfolios under different models.

	3-factor model					4-factor model				
Quarter	*IAV1*	*IAV2*	*IAV3*	*IAV4*	*IAV5*	*IAV1*	*IAV2*	*IAV3*	*IAV4*	*IAV5*
Q4 2006	58	40	45	48	64	56	45	44	46	64
Q3 2006	66	59	46	39	40	65	52	53	40	40
Q2 2006	21	54	40	61	70	21	55	42	59	69
Q1 2006	44	41	64	49	46	47	38	64	47	48
Q4 2005	79	37	26	38	64	79	37	28	36	64
Q3 2005	22	55	88	52	26	22	63	73	56	29
Q2 2005	60	43	44	44	51	59	46	41	46	50
Q1 2005	32	42	60	45	59	33	41	57	53	54
Q4 2004	65	33	34	45	58	67	35	29	46	58
Q3 2004	41	70	41	50	32	43	72	39	51	29
Q2 2004	46	35	61	40	51	44	38	59	41	51
Q1 2004	41	69	53	30	39	41	75	49	30	37
Q4 2003	45	45	37	56	49	46	43	36	52	55
Q3 2003	48	47	58	35	43	47	46	57	37	44
Q2 2003	35	32	41	46	77	36	33	33	52	77
Q1 2003	51	40	39	56	39	46	43	45	45	46
Q4 2002	28	50	70	41	36	27	46	77	43	32
Q3 2002	72	52	29	34	37	66	51	37	31	39
Q2 2002	36	33	33	51	66	32	37	34	43	73
Q1 2002	46	53	52	24	37	50	47	52	28	35
Q4 2001	29	50	40	57	35	31	54	37	54	34
Q3 2001	46	46	34	46	38	45	40	40	44	41
Q2 2001	52	30	41	40	43	53	33	35	48	37
Q1 2001	28	27	47	51	40	25	34	41	49	43
Q4 2000	42	55	30	32	29	47	55	27	29	30
Q3 2000	49	25	22	42	46	46	27	21	45	45
Q2 2000	24	37	37	47	35	27	34	44	39	36
Q1 2000	34	38	38	29	31	30	50	32	26	32
Q4 1999	39	30	25	26	40	39	27	26	26	42
Q3 1999	21	22	43	37	32	23	19	41	41	31
Q2 1999	27	30	20	35	38	32	25	18	40	34
Q1 1999	26	28	33	24	26	26	30	28	31	22
Q4 1998	31	34	23	27	23	31	30	26	25	26
Q3 1998	26	28	23	17	35	22	32	24	16	34
Q2 1998	26	19	20	24	34	28	18	21	24	32
Q1 1998	21	23	23	16	17	20	22	24	19	15
Q4 1997	22	13	26	13	27	14	21	24	15	27
Q3 1997	21	14	13	17	19	20	15	11	14	24
Q2 1997	11	26	18	13	17	13	23	19	11	19

TABLE 8 – LARGE-CAP IAR PORTFOLIOS

Distribution of observations over time for the quintile *IAR* portfolios when restricting the sample to large-cap stocks only.

	4-factor model				
Quarter	*IAV1*	*IAV2*	*IAV3*	*IAV4*	*IAV5*
Q4 2006	11	5	12	18	19
Q3 2006	17	14	17	7	8
Q2 2006	9	11	16	8	19
Q1 2006	9	9	18	16	11
Q4 2005	22	9	6	7	19
Q3 2005	7	10	14	20	12
Q2 2005	15	12	12	10	14
Q1 2005	11	9	21	10	12
Q4 2004	16	11	11	9	14
Q3 2004	9	20	5	13	13
Q2 2004	12	9	6	15	18
Q1 2004	12	12	18	12	6
Q4 2003	11	14	5	15	15
Q3 2003	9	13	14	14	9
Q2 2003	11	12	7	17	12
Q1 2003	8	14	10	20	5
Q4 2002	5	8	19	13	12
Q3 2002	23	11	9	5	9
Q2 2002	11	6	9	15	15
Q1 2002	10	10	13	7	14
Q4 2001	17	11	8	10	8
Q3 2001	8	8	10	17	11
Q2 2001	9	12	8	7	17
Q1 2001	5	18	10	9	9
Q4 2000	14	15	7	8	6
Q3 2000	11	6	9	8	15
Q2 2000	10	8	3	13	15
Q1 2000	1	18	16	4	9
Q4 1999	12	6	10	10	8
Q3 1999	8	6	9	5	17
Q2 1999	7	10	8	14	6
Q1 1999	11	7	9	11	6
Q4 1998	9	10	7	9	9
Q3 1998	8	12	10	1	11
Q2 1998	7	6	7	11	10
Q1 1998	8	10	3	12	3
Q4 1997	5	9	2	13	8
Q3 1997	11	7	4	2	10
Q2 1997	4	9	11	7	6

TABLE 9 – LARGE-CAP IAV PORTFOLIOS

Distribution of observations over time for the quintile *IAV* portfolios when restricting the sample to large-cap stocks only.

	4-factor model				
Quarter	*IAV1*	*IAV2*	*IAV3*	*IAV4*	*IAV5*
Q4 2006	15	10	17	14	9
Q3 2006	17	7	13	9	17
Q2 2006	5	11	21	17	9
Q1 2006	7	3	18	15	20
Q4 2005	27	4	15	7	10
Q3 2005	11	15	13	12	12
Q2 2005	19	13	9	17	5
Q1 2005	4	10	13	20	16
Q4 2004	16	16	9	8	12
Q3 2004	13	16	6	13	12
Q2 2004	12	14	12	11	11
Q1 2004	7	14	16	23	0
Q4 2003	14	9	12	10	15
Q3 2003	9	16	6	8	20
Q2 2003	15	14	10	12	8
Q1 2003	7	10	8	22	10
Q4 2002	11	14	12	9	11
Q3 2002	22	8	7	4	16
Q2 2002	9	10	16	17	4
Q1 2002	12	7	8	8	19
Q4 2001	7	15	17	9	6
Q3 2001	9	8	11	7	19
Q2 2001	6	11	15	16	5
Q1 2001	9	14	6	5	17
Q4 2000	14	16	10	4	6
Q3 2000	17	2	10	5	15
Q2 2000	8	12	8	6	15
Q1 2000	15	12	18	2	1
Q4 1999	3	9	8	6	20
Q3 1999	12	8	9	4	12
Q2 1999	4	7	4	12	18
Q1 1999	7	11	11	7	8
Q4 1998	17	5	11	6	5
Q3 1998	4	10	6	8	14
Q2 1998	7	22	2	4	6
Q1 1998	7	0	9	10	10
Q4 1997	9	10	3	4	11
Q3 1997	4	10	15	2	3
Q2 1997	7	9	3	12	6

TABLE 10 – COMBINED PORTFOLIOS

This table presents the number of observations for the three different sorting algorithms used in forming the portfolios for the combined *IAR*/*IAV* strategy. The number of observations are not uniformly distributed (i.e. one fifth into every quintile) because we use data for the announcement period preceding the current period to calculate "best guess" quintile breakpoints for the actual breakpoints for the current period. The purpose of this is to ensure that the strategies actually can be implemented. In contrast, using data from the current period would require knowing the outcomes from all earnings announcements even though the announcements do not take place simultaneously, and thus would lead to look-ahead bias. The difference in total observations between the independent sorting and the other two algorithms is due to the fact that we need portfolios from a preceding announcement period when calculating dependent cutoffs. Hence we get 1 less announcement period (the Q1 1998 period with 85 observations) when forming portfolios by dependent sorting.

4-factor model

Independent sorting

	IAV1	*IAV2*	*IAV3*	*IAV4*	*IAV5*	Σ
IAR1	584	311	255	189	160	1499
IAR2	218	290	298	377	349	1532
IAR3	141	199	267	386	495	1488
IAR4	187	297	321	352	321	1478
IAR5	508	366	303	247	174	1598
Σ	1638	1463	1444	1551	1499	7595

Sorting *IAV* dependent on *IAR*

	IAV1	*IAV2*	*IAV3*	*IAV4*	*IAV5*	Σ
IAR1	327	294	262	248	355	1486
IAR2	103	150	248	321	687	1509
IAR3	60	106	165	305	833	1469
IAR4	83	148	242	348	646	1467
IAR5	255	305	302	328	389	1579
Σ	828	1003	1219	1550	2910	7510

Sorting *IAR* dependent on *IAV*

	IAV1	*IAV2*	*IAV3*	*IAV4*	*IAV5*	Σ
IAR1	349	119	85	61	59	673
IAR2	288	265	240	248	196	1237
IAR3	336	433	511	595	726	2601
IAR4	266	376	406	431	384	1863
IAR5	380	247	187	198	124	1136
Σ	1619	1440	1429	1533	1489	7510

TABLE 11 – INDEPENDENT COMBINED STRATEGIES

Average *CAR* in percent per annum and *t*-statistic for 13 holding periods. Days are trading days. *IAR* (*IAV*) Spread is the difference between the *IAR1* and *IAR5* (IAV1 and IAV5) portfolios respectively, equivalent to the return to a market risk-neutral long/short strategy. ** (*) represents significance at 1% (5%) level.

4-Factor Model, independent sorting

1	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
day	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.64**	3.08	1.68*	2.27	1.02	1.18	-.07	-.05	-2.85	-1.38	4.49*	2.11
IAR2	1.04	1.35	.01	.01	.04	.06	.24	.41	-.12	-.18	1.16	1.14
IAR3	.51	.60	-.90	-1.22	-.93	-1.35	-.07	-.09	-1.31*	-2.26	1.82	1.76
IAR4	-1.30	-1.40	-.80	-1.12	-1.18	-1.78	-1.14	-1.66	.05	.07	-1.36	-1.10
IAR5	-1.22	-1.78	-3.90**	-4.62	-2.20*	-2.13	-1.12	-.98	.89	.35	-2.10	-.80
IAR Spread	2.86**	3.30	5.58**	4.96	3.22*	2.39	1.05	.55	-3.73	-1.14		

5	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	.84	.70	.47	.28	-1.15	-.60	-3.75	-1.09	-5.43	-1.18	6.26	1.32
IAR2	3.77*	2.19	-1.15	-.85	-.78	-.52	-.31	-.24	-1.47	-.98	5.24*	2.30
IAR3	-2.36	-1.23	-.13	-.08	-2.56	-1.66	-1.45	-.86	-3.29*	-2.55	.93	.40
IAR4	-3.45	-1.66	-.44	-.28	-1.53	-1.03	-2.97	-1.94	-.22	-.12	-3.23	-1.18
IAR5	-1.44	-.94	-4.26*	-2.26	-4.43	-1.91	-5.68*	-2.23	.70	.12	-2.14	-.36
IAR Spread	2.27	1.17	4.73	1.88	3.28	1.09	1.93	.45	-6.13	-.84		

4-Factor Model, independent sorting

10	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.36	.81	-.08	-.03	-.52	-.19	-6.90	-1.42	-5.25	-.81	6.61	.98
IAR2	4.16	1.70	-.80	-.42	-.87	-.41	4.63*	2.49	-1.77	-.84	5.93	1.84
IAR3	-.33	-.12	-.73	-.31	-2.47	-1.14	-.61	-.25	-2.23	-1.22	1.90	.58
IAR4	-3.31	-1.13	-.80	-.36	-2.24	-1.07	-2.26	-1.04	-.12	-.05	-3.19	-.82
IAR5	-1.94	-.90	-5.41*	-2.02	-3.90	-1.19	-7.00	-1.94	3.34	.42	-5.28	-.63
IAR Spread	3.30	1.20	5.33	1.50	3.39	.79	.10	.02	-8.59	-.83		

4-Factor Model, independent sorting

15	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.97	.95	.36	.13	-.03	-.01	-5.67	-.95	-7.21	-.90	9.18	1.11
IAR2	4.05	1.36	-2.17	-.93	.12	.05	4.33	1.90	.02	.01	4.02	1.02
IAR3	2.40	.72	-.08	-.03	-2.98	-1.12	1.89	.64	-1.85	-.83	4.25	1.06
IAR4	-2.93	-.81	-1.46	-.53	-.50	-.19	-2.06	-.77	-.65	-.21	-2.28	-.48
IAR5	1.30	.49	-5.16	-1.58	-3.58	-.89	-6.60	-1.49	-2.02	-.21	3.32	.33
IAR Spread	.66	.20	5.53	1.27	3.54	.68	.93	.13	-5.20	-.41		

TABLE 11 (CONT.)

4-Factor Model, independent sorting

20 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.80	.76	-.36	-.11	-.37	-.10	-7.53	-1.10	-5.28	-.57	7.09	.74
IAR2	6.50	1.88	-2.71	-1.01	-1.07	-.36	3.90	1.48	-.35	-.12	6.85	1.50
IAR3	2.00	.52	-2.36	-.72	-4.25	-1.38	1.52	.45	-3.52	-1.36	5.51	1.19
IAR4	-.58	-.14	-1.69	-.53	-.33	-.11	-3.35	-1.09	-.03	-.01	-.56	-.10
IAR5	2.28	.75	-3.71	-.98	-4.94	-1.07	-9.34	-1.83	4.09	.36	-1.81	-.15
IAR Spread	-.48	-.12	3.35	.67	4.57	.76	1.82	.21	-9.38	-.64		

4-Factor Model, independent sorting

25 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	2.71	1.02	-1.47	-.40	-1.42	-.33	1.75	.23	-5.89	-.57	8.60	.81
IAR2	6.56	1.70	-2.80	-.93	-2.29	-.69	3.35	1.14	1.59	.48	4.97	.98
IAR3	2.69	.63	-2.87	-.78	-3.04	-.88	.96	.25	-2.82	-.98	5.51	1.07
IAR4	-.82	-.18	-3.44	-.96	1.09	.33	-3.08	-.90	.27	.07	-1.09	-.18
IAR5	3.71	1.08	-4.78	-1.13	-7.52	-1.45	-12.63*	-2.21	3.39	.27	.32	.02
IAR Spread	-1.00	-.23	3.31	.59	6.09	.90	14.38	1.50	-9.28	-.57		

4-Factor Model, independent sorting

30 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	3.00	1.03	-1.63	-.40	.89	.19	.30	.04	-5.72	-.51	8.72	.75
IAR2	6.26	1.48	-4.51	-1.37	-2.85	-.78	5.99	1.85	3.92	1.07	2.33	.42
IAR3	2.83	.60	-3.25	-.81	-4.46	-1.18	-.69	-.17	-4.10	-1.30	6.93	1.23
IAR4	-3.76	-.74	-4.00	-1.02	.02	.00	-3.96	-1.05	-.58	-.13	-3.18	-.47
IAR5	1.94	.52	-6.32	-1.37	-10.22	-1.80	-15.80*	-2.53	-3.03	-.22	4.97	.35
IAR Spread	1.06	.22	4.69	.76	11.11	1.50	16.11	1.54	-2.69	-.15		

4-Factor Model, independent sorting

35 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	2.04	.65	-1.01	-.23	.87	.17	.65	.07	-5.44	-.45	7.48	.59
IAR2	6.54	1.43	-2.54	-.72	-5.57	-1.42	4.47	1.28	5.33	1.35	1.20	.20
IAR3	4.80	.95	-3.33	-.77	-3.57	-.88	-.19	-.04	-4.16	-1.22	8.97	1.47
IAR4	-3.13	-.57	-5.56	-1.32	-1.48	-.38	-5.07	-1.25	-1.48	-.31	-1.65	-.23
IAR5	1.81	.45	-8.67	-1.73	-11.04	-1.80	-19.33**	-2.86	-.17	-.01	1.98	.13
IAR Spread	.23	.05	7.66	1.15	11.91	1.49	19.98	1.77	-5.27	-.27		

TABLE 11 (CONT.)

4-factor model, independent sorting

40 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	3.33	.99	-.56	-.12	.37	.07	-1.65	-.17	-5.84	-.45	9.17	.68
IAR2	6.29	1.29	-3.47	-.91	-5.38	-1.28	3.79	1.02	5.67	1.34	.63	.10
IAR3	6.08	1.12	-2.07	-.45	-4.85	-1.11	-1.51	-.32	-3.60	-.99	9.68	1.48
IAR4	-3.47	-.59	-6.42	-1.42	-2.12	-.51	-5.78	-1.33	-1.12	-.22	-2.35	-.30
IAR5	2.10	.49	-7.45	-1.39	-12.83*	-1.96	-20.21**	-2.80	-8.63	-.54	10.73	.65
IAR Spread	1.23	.22	6.88	.97	13.20	1.55	18.56	1.54	2.79	.13		

4-factor model, independent sorting

45 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	2.76	.82	-2.27	-.48	.06	.01	-.10	-.01	-6.47	-.50	9.22	.69
IAR2	7.52	1.54	-3.35	-.88	-5.05	-1.20	4.54	1.22	6.35	1.50	1.17	.18
IAR3	7.09	1.31	-.84	-.18	-7.73	-1.78	-.81	-.17	-3.40	-.93	10.49	1.61
IAR4	-1.98	-.34	-6.06	-1.34	.02	.01	-2.92	-.67	-.45	-.09	-1.53	-.20
IAR5	1.02	.23	-9.31	-1.74	-10.28	-1.57	-21.43**	-2.97	-5.68	-.35	6.69	.40
IAR Spread	1.74	.32	7.04	.99	10.34	1.21	21.33	1.76	-.79	-.04		

4-factor model, independent sorting

50 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	3.38	.90	-.90	-.17	.98	.16	-.70	-.06	-6.27	-.43	9.66	.64
IAR2	8.01	1.47	-2.68	-.63	-5.00	-1.06	4.29	1.03	6.63	1.41	1.37	.19
IAR3	6.34	1.05	-1.43	-.28	-5.56	-1.14	.15	.03	-5.54	-1.36	11.88	1.63
IAR4	-3.02	-.46	-4.34	-.86	.22	.05	-2.93	-.60	.94	.17	-3.95	-.46
IAR5	.53	.11	-7.47	-1.25	-7.22	-.99	-19.63*	-2.43	-4.05	-.23	4.58	.25
IAR Spread	2.85	.46	6.57	.83	8.20	.86	18.93	1.40	-2.22	-.10		

4-factor model, independent sorting

55 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	4.01	1.02	-.31	-.06	1.73	.27	-1.45	-.13	-8.98	-.59	13.00	.82
IAR2	6.85	1.20	-2.05	-.46	-4.89	-.99	2.17	.50	7.16	1.45	-.31	-.04
IAR3	7.49	1.18	.09	.02	-6.05	-1.19	.08	.01	-4.39	-1.02	11.88	1.55
IAR4	-5.19	-.75	-3.87	-.73	-.51	-.10	-3.08	-.61	1.66	.28	-6.85	-.75
IAR5	1.77	.35	-7.17	-1.14	-6.03	-.79	-20.03*	-2.37	-1.51	-.08	3.27	.17
IAR Spread	2.25	.35	6.86	.82	7.75	.78	18.58	1.31	-7.48	-.31		

TABLE 11 (CONT.)

4-factor model, independent sorting

60 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	4.30	1.04	-.58	-.10	2.12	.32	-4.13	-.35	-7.27	-.46	11.57	.70
IAR2	7.62	1.27	-1.60	-.34	-4.38	-.85	3.28	.72	9.31	1.80	-1.70	-.21
IAR3	9.24	1.39	.14	.02	-6.38	-1.20	-1.70	-.29	-3.27	-.73	12.51	1.56
IAR4	-5.57	-.77	-5.09	-.92	.80	.16	-2.50	-.47	1.73	.28	-7.31	-.77
IAR5	3.53	.67	-5.00	-.76	9.11	1.14	-18.43*	-2.09	-1.41	-.07	4.94	.24
IAR Spread	.77	.11	4.42	.51	-6.99	-.67	14.31	.97	-5.86	-.23		

TABLE 12 – IAR-DEPENDENT COMBINED STRATEGIES

Average *CAR* in percent per annum and *t*-statistic for 13 holding periods. Days are trading days. *IAR* (*IAV*) Spread is the difference between the *IAR1* and *IAR5* (*IAV1* and *IAV5*) portfolios respectively, equivalent to the return to a market risk-neutral long/short strategy ** (*) represents significance at 1% (5%) level.

4-factor model, sorting *IAV* dependent on *IAR*

1 day	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	3.43**	4.45	.45	.65	2.04*	2.54	1.54	1.50	-2.37*	-2.01	5.80**	4.11
IAR2	3.45**	2.98	-.74	-.85	.55	.83	1.27*	2.02	.34	.74	3.11*	2.49
IAR3	.21	.14	.65	.74	-1.13	-1.32	-1.15	-1.80	-1.67**	-3.46	1.88	1.21
IAR4	-1.17	-.75	-3.02**	-3.16	-1.61*	-2.07	-2.16**	-3.29	-.64	-1.19	-.54	-.33
IAR5	-2.04*	-2.17	-1.57	-1.72	-6.08**	-6.36	-1.61	-1.79	-.37	-.27	-1.67	-1.01
IAR Spread	5.48**	4.50	2.03	1.76	8.12**	6.50	3.15*	2.30	-2.00	-1.11		

4-factor model, sorting *IAV* dependent on *IAR*

5 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.00	.58	-.91	-.59	-1.10	-.61	-3.29	-1.43	-4.01	-1.52	5.01	1.59
IAR2	3.80	1.47	-.10	-.05	-.31	-.21	-.21	-.15	-.42	-.41	4.22	1.51
IAR3	-3.77	-1.15	-.71	-.36	-.14	-.07	-2.17	-1.51	-3.14**	-2.91	-.64	-.18
IAR4	-5.44	-1.56	-3.61	-1.69	-.63	-.36	-1.49	-1.02	-1.32	-1.11	-4.12	-1.12
IAR5	.25	.12	-1.13	-.55	-4.68*	-2.19	-3.15	-1.57	-2.22	-.73	2.47	.67
IAR Spread	.75	.28	.22	.08	3.58	1.28	-.15	-.05	-1.79	-.44		

4-factor model, sorting *IAV* dependent on *IAR*

10 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.70	.70	-1.09	-.50	-1.24	-.49	-3.96	-1.21	-8.19*	-2.19	9.89*	2.22
IAR2	7.49*	2.05	1.50	.55	.58	.27	-1.20	-.60	-.60	-.41	8.09*	2.05
IAR3	-6.38	-1.37	3.26	1.17	-2.25	-.83	-3.48	-1.71	-2.67	-1.75	-3.71	-.76
IAR4	-7.34	-1.49	-2.92	-.96	-3.77	-1.54	-3.27	-1.57	-2.62	-1.55	-4.72	-.91
IAR5	-1.38	-.46	-4.38	-1.51	-8.12**	-2.69	-3.16	-1.11	-.15	-.03	-1.23	-.25
IAR Spread	3.08	.80	3.29	.91	6.88	1.74	-.80	-.18	-8.04	-1.41		

4-factor model, sorting *IAV* dependent on *IAR*

15 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.03	.35	.35	.13	-.19	-.06	-3.53	-.88	-5.65	-1.24	6.69	1.22
IAR2	4.97	1.11	.16	.05	-.38	-.15	.10	.04	.86	.48	4.11	.85
IAR3	-2.27	-.40	5.93	1.74	-.12	-.04	-3.53	-1.42	-.60	-.32	-1.66	-.28
IAR4	-5.95	-.99	-2.10	-.57	-1.74	-.58	-2.51	-.99	-2.75	-1.32	-3.21	-.50
IAR5	6.50	1.78	-1.50	-.42	-7.36*	-1.99	-.53	-.15	-1.56	-.30	8.06	1.26
IAR Spread	-5.47	-1.16	1.86	.42	7.17	1.48	-3.01	-.57	-4.09	-.59		

TABLE 12 (CONT.)

4-factor model, sorting *IAV* dependent on *IAR*

20 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	.48	.14	-.86	-.28	-1.45	-.40	-6.02	-1.30	-5.40	-1.02	5.88	.93
IAR2	10.15*	1.96	-1.22	-.31	-.89	-.30	-.13	-.05	.34	.16	9.81	1.76
IAR3	-1.80	-.27	5.84	1.49	-2.84	-.74	-4.31	-1.50	-1.97	-.91	.17	.02
IAR4	-4.98	-.72	.25	.06	-3.07	-.88	-2.39	-.82	-2.52	-1.05	-2.47	-.34
IAR5	9.73*	2.31	1.02	.25	-6.04	-1.41	-2.82	-.70	.45	.07	9.28	1.25
IAR Spread	-9.25	-1.70	-1.88	-.37	4.59	.82	-3.20	-.52	-5.85	-.72		

4-factor model, sorting *IAV* dependent on *IAR*

25 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.93	.50	-2.28	-.66	-2.34	-.58	-6.14	-1.19	-.65	-.11	2.58	.37
IAR2	9.72	1.68	-.79	-.18	-.61	-.18	-1.41	-.45	1.93	.84	7.79	1.25
IAR3	-2.64	-.36	6.16	1.40	-1.46	-.34	-5.96	-1.86	-.93	-.38	-1.71	-.22
IAR4	-7.64	-.98	-.01	.00	-2.39	-.62	-1.67	-.51	-2.36	-.88	-5.27	-.64
IAR5	11.06*	2.35	1.49	.33	-10.40*	-2.18	-5.10	-1.14	-.99	-.14	12.05	1.45
IAR Spread	-9.13	-1.50	-3.77	-.66	8.06	1.29	-1.04	-.15	.34	.04		

4-factor model, sorting *IAV* dependent on *IAR*

30 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.28	.30	1.24	.33	-.25	-.06	-1.87	-.33	-3.10	-.48	4.38	.57
IAR2	10.13	1.60	-2.12	-.45	-3.03	-.83	-1.89	-.55	5.98*	2.36	4.15	.61
IAR3	-4.12	-.51	6.37	1.33	-1.76	-.37	-6.25	-1.78	-2.22	-.84	-1.90	-.22
IAR4	-7.47	-.88	-1.00	-.19	-3.20	-.75	-2.43	-.68	-3.22	-1.10	-4.25	-.47
IAR5	7.29	1.41	.95	.19	-13.11*	-2.50	-7.30	-1.48	-6.02	-.81	13.31	1.47
IAR Spread	-6.01	-.90	.29	.05	12.86	1.88	5.43	.72	2.92	.30		

4-factor model, sorting *IAV* dependent on *IAR*

35 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.09	.24	-1.13	-.28	.62	.13	-3.28	-.54	-2.41	-.34	3.50	.42
IAR2	12.28	1.79	-2.51	-.49	-2.26	-.57	-3.05	-.82	6.97*	2.55	5.31	.72
IAR3	-.68	-.08	5.93	1.14	-2.73	-.54	-7.43	-1.96	-1.77	-.62	1.09	.12
IAR4	-7.24	-.79	-.88	-.16	-4.24	-.92	-4.27	-1.10	-4.40	-1.39	-2.84	-.29
IAR5	8.90	1.60	-.87	-.16	-12.00*	-2.12	-10.27	-1.93	-6.73	-.83	15.63	1.59
IAR Spread	-7.81	-1.08	-.27	-.04	12.62	1.71	6.99	.86	4.32	.40		

TABLE 12 (CONT.)

4-factor model, sorting IAV dependent on IAR

40 days	$IAV1$		$IAV2$		$IAV3$		$IAV4$		$IAV5$		IAV Spread	
	CAR	t	CAR	t	CAR	t	CAR	t	CAR	t	CAR	t
$IAR1$	2.67	.55	-.32	-.07	.04	.01	-3.85	-.59	-4.19	-.56	6.87	.77
$IAR2$	13.10	1.79	-2.72	-.49	-3.04	-.72	-4.31	-1.08	6.31*	2.16	6.79	.86
$IAR3$	-.97	-.10	8.63	1.56	-1.81	-.33	-8.11*	-2.00	-1.93	-.63	.96	.10
$IAR4$	-8.18	-.83	-2.45	-.41	-4.66	-.95	-4.71	-1.13	-5.17	-1.53	-3.02	-.29
$IAR5$	10.04	1.69	-2.59	-.45	-11.31	-1.87	-12.22*	-2.15	-10.34	-1.20	20.39	1.94
IAR Spread	-7.37	-.96	2.27	.31	11.36	1.44	8.37	.97	6.15	.54		

4-factor model, sorting IAV dependent on IAR

45 days	$IAV1$		$IAV2$		$IAV3$		$IAV4$		$IAV5$		IAV Spread	
	CAR	t	CAR	t	CAR	t	CAR	t	CAR	t	CAR	t
$IAR1$	2.58	.94	-.66	-.16	-2.69	-.51	-1.71	-.20	-4.24	-.26	6.82	.41
$IAR2$	15.58**	4.51	-3.16	-1.11	-2.84	-.81	-5.68	-1.68	7.13	1.24	8.45	1.26
$IAR3$	.05	.01	9.67**	3.27	-1.12	-.33	-9.21**	-2.87	-1.38	-.27	1.43	.22
$IAR4$	-4.32	-.99	-1.58	-.52	-3.27	-.88	-3.79	-.92	-3.61	-.53	-.72	-.09
$IAR5$	11.06**	3.70	-4.53	-.94	-12.67*	-2.10	-9.50	-1.26	-10.29	-.53	21.36	1.09
IAR Spread	-8.49*	-2.10	3.87	.61	9.98	1.25	7.79	.68	6.05	.24		

4-factor model, sorting IAV dependent on IAR

50 days	$IAV1$		$IAV2$		$IAV3$		$IAV4$		$IAV5$		IAV Spread	
	CAR	t	CAR	t	CAR	t	CAR	t	CAR	t	CAR	t
$IAR1$	2.45	.45	.27	.06	-1.24	-.22	-2.56	-.35	-3.97	-.48	6.42	.64
$IAR2$	18.33*	2.24	-3.70	-.60	-1.79	-.38	-4.86	-1.09	7.80*	2.39	10.53	1.19
$IAR3$	.14	.01	10.15	1.64	-1.32	-.22	-7.76	-1.71	-3.09	-.91	3.23	.30
$IAR4$	-3.15	-.29	-2.36	-.35	-3.85	-.70	-2.39	-.52	-3.09	-.82	-.06	.00
$IAR5$	12.60	1.89	-7.18	-1.11	-11.05	-1.63	-8.02	-1.26	-7.85	-.81	20.45	1.74
IAR Spread	-10.15	-1.18	7.45	.92	9.81	1.11	5.45	.56	3.88	.30		

4-factor model, sorting IAV dependent on IAR

55 days	$IAV1$		$IAV2$		$IAV3$		$IAV4$		$IAV5$		IAV Spread	
	CAR	t	CAR	t	CAR	t	CAR	t	CAR	t	CAR	t
$IAR1$	2.29	.40	1.47	.29	-.69	-.12	-1.87	-.24	-5.51	-.63	7.79	.75
$IAR2$	17.36*	2.02	-2.57	-.40	-2.64	-.54	-4.78	-1.02	8.02*	2.34	9.34	1.01
$IAR3$	2.65	.24	8.09	1.24	-1.45	-.23	-7.32	-1.54	-2.23	-.62	4.88	.42
$IAR4$	-4.45	-.39	-4.01	-.56	-5.43	-.94	-3.46	-.71	-2.90	-.73	-1.54	-.13
$IAR5$	13.43	1.92	-7.45	-1.10	-9.92	-1.40	-6.30	-.95	-7.71	-.76	21.14	1.72
IAR Spread	-11.14	-1.23	8.92	1.05	9.23	1.00	4.42	.44	2.20	.16		

TABLE 12 (CONT.)

4-factor model, sorting *IAV* dependent on *IAR*

60 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	2.09	.35	2.10	.39	-.27	-.04	-3.36	-.42	-5.27	-.58	7.35	.67
IAR2	20.05*	2.24	-2.43	-.36	-3.37	-.65	-4.39	-.90	9.92**	2.77	10.13	1.05
IAR3	5.20	.46	8.21	1.21	-1.84	-.28	-8.56	-1.72	-1.60	-.43	6.80	.57
IAR4	-2.61	-.22	-5.68	-.77	-4.11	-.68	-2.88	-.57	-2.95	-.71	.34	.03
IAR5	17.05*	2.34	-4.93	-.69	-8.76	-1.18	5.80	.83	-6.47	-.61	23.52	1.83
IAR Spread	-14.96	-1.59	7.02	.79	8.49	.88	-9.16	-.86	1.21	.09		

TABLE 13 – IAV-DEPENDENT COMBINED STRATEGIES

Average *CAR* in percent per annum and *t*-statistic for 13 holding periods. Days are trading days. *IAR* (*IAV*) Spread is the difference between the *IAR1* and *IAR5* (*IAV1* and *IAV5*) portfolios respectively, equivalent to the return to a market risk-neutral long/short strategy.
** (*) represents significance at 1% (5%) level.

4-factor model, sorting *IAR* dependent on *IAV*

1	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
day	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	2.60**	3.43	2.72**	5.34	1.99**	3.26	.18	.15	-4.69*	-2.51	7.29**	3.62
IAR2	2.84**	3.23	3.34**	5.13	-.29	-.47	.51	.87	-1.66**	-3.14	4.51**	4.38
IAR3	.29	.20	-.32	-.28	-.39	-.40	-.26	-.29	-.74	-1.06	1.03	.64
IAR4	-2.12*	-1.98	-1.81*	-2.24	-.91	-1.04	-2.25**	-2.62	.32	.36	-2.44	-1.76
IAR5	-.85	-1.36	-4.15**	-5.56	-2.75**	-3.35	-1.89*	-2.06	-1.18	-.49	.33	.13
IAR Spread	3.45**	3.51	6.87**	7.60	4.74**	4.63	2.07	1.39	-3.50	-1.14		

4-factor model, sorting *IAR* dependent on *IAV*

5	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	.13	.08	-.50	-.17	-1.20	-.29	-7.99	-.98	-16.96	-1.50	17.09	1.49
IAR2	4.52**	3.03	-1.18	-.74	-.76	-.45	-2.03	-1.01	-4.17*	-1.97	8.68**	3.36
IAR3	1.63	1.20	-1.31	-1.12	-2.19	-1.96	-1.33	-1.05	-4.19**	-3.90	5.82**	3.36
IAR4	-1.60	-.95	-1.22	-.85	-1.55	-1.00	-6.64**	-4.24	-1.55	-.93	-.06	-.02
IAR5	-3.16	-1.69	-2.78	-1.13	-5.65	-1.90	-6.16*	-2.40	-5.64	-.74	2.48	.32
IAR Spread	3.29	1.30	2.29	.59	4.45	.88	-1.83	-.21	-11.32	-.83		

4-factor model, sorting *IAR* dependent on *IAV*

10	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.32	.55	-.38	-.09	1.44	.25	-14.61	-1.27	-16.38	-1.02	17.71	1.09
IAR2	5.09*	2.41	-1.25	-.55	-.34	-.14	-2.11	-.74	-6.08*	-2.04	11.17**	3.06
IAR3	2.74	1.43	-.99	-.60	-3.43*	-2.17	2.51	1.39	-4.64**	-3.05	7.38**	3.01
IAR4	-1.31	-.55	-2.04	-1.01	-2.40	-1.09	-6.94**	-3.14	.95	.40	-2.26	-.68
IAR5	-4.60	-1.74	-2.88	-.82	-2.45	-.58	-8.10*	-2.23	5.01	.46	-9.61	-.86
IAR Spread	5.92	1.66	2.50	.46	3.89	.54	-6.51	-.54	-21.39	-1.11		

4-factor model, sorting *IAR* dependent on *IAV*

15	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
days	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.53	.52	3.74	.73	.58	.08	-7.81	-.56	-11.51	-.59	13.04	.66
IAR2	3.81	1.48	-1.50	-.54	.36	.12	.52	.15	-3.62	-.99	7.44	1.66
IAR3	3.63	1.54	-1.62	-.80	-1.39	-.72	2.73	1.24	-1.54	-.83	5.17	1.72
IAR4	.60	.21	.13	.05	-1.55	-.58	-3.52	-1.30	-2.12	-.74	2.71	.66
IAR5	.95	.29	-5.22	-1.22	-.72	-.14	-7.55	-1.70	4.23	.32	-3.28	-.24
IAR Spread	.58	.13	8.96	1.34	1.30	.15	-.26	-.02	-15.74	-.67		

TABLE 13 (CONT.)

4-factor model, sorting *IAR* dependent on *IAV*

20 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.52	.45	3.31	.56	1.91	.23	-14.65	-.90	-6.72	-.30	8.24	.36
IAR2	3.66	1.23	-2.41	-.76	-2.19	-.65	.24	.06	-2.60	-.62	6.26	1.21
IAR3	5.36*	1.97	-3.57	-1.53	-2.26	-1.01	2.85	1.12	-2.29	-1.07	7.65*	2.21
IAR4	1.45	.43	.35	.12	-2.16	-.70	-6.95*	-2.22	.17	.05	1.28	.27
IAR5	.71	.19	-2.60	-.53	-3.31	-.56	-11.15*	-2.17	10.34	.68	-9.62	-.61
IAR Spread	.81	.16	5.91	.76	5.22	.52	-3.50	-.21	-17.06	-.63		

4-factor model, sorting *IAR* dependent on *IAV*

25 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	2.95	.78	1.91	.29	-.61	-.07	-14.19	-.78	-9.30	-.37	12.25	.48
IAR2	2.96	.89	-1.90	-.53	-2.48	-.66	4.39	.97	-1.73	-.37	4.69	.81
IAR3	5.88	1.94	-4.42	-1.69	-2.39	-.96	3.03	1.07	-.84	-.35	6.71	1.73
IAR4	-.02	-.01	-.71	-.22	-2.81	-.81	-8.52*	-2.43	1.35	.37	-1.37	-.26
IAR5	3.71	.89	-6.22	-1.13	-4.70	-.71	-16.65**	-2.90	6.45	.38	-2.74	-.16
IAR Spread	-.77	-.14	8.13	.94	4.09	.36	2.45	.13	-15.75	-.52		

4-factor model, sorting *IAR* dependent on *IAV*

30 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	2.57	.62	2.39	.33	4.90	.49	-16.24	-.82	-7.84	-.28	10.41	.37
IAR2	4.11	1.12	-3.09	-.79	-1.39	-.34	1.75	.35	-1.57	-.30	5.67	.90
IAR3	5.86	1.76	-5.98*	-2.09	-3.30	-1.21	3.43	1.10	1.39	.53	4.47	1.05
IAR4	-3.44	-.84	1.61	.46	-4.43	-1.16	-9.40*	-2.45	1.60	.39	-5.04	-.87
IAR5	2.88	.63	-9.61	-1.59	-7.92	-1.09	-18.90**	-3.01	-.53	-.03	3.41	.18
IAR Spread	-.32	-.05	12.00	1.27	12.83	1.04	2.66	.13	-7.31	-.22		

4-factor model, sorting *IAR* dependent on *IAV*

35 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	.59	.13	4.98	.63	4.98	.46	-13.71	-.64	-9.37	-.31	9.96	.33
IAR2	3.80	.96	-2.17	-.52	-1.95	-.44	.51	.09	-1.05	-.19	4.84	.71
IAR3	6.28	1.75	-5.72	-1.85	-5.36	-1.81	1.67	.50	2.19	.77	4.09	.89
IAR4	-2.79	-.63	-1.85	-.49	-5.30	-1.29	-12.12**	-2.93	1.26	.29	-4.05	-.65
IAR5	3.28	.66	-11.24	-1.72	-11.23	-1.43	-22.54**	-3.32	5.26	.26	-1.98	-.10
IAR Spread	-2.69	-.40	16.22	1.59	16.21	1.21	8.83	.39	-14.63	-.41		

TABLE 13 (CONT.)

4-factor model, sorting *IAR* dependent on *IAV*

40 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	2.10	.44	5.97	.71	3.83	.33	-11.84	-.52	-15.03	-.47	17.13	.53
IAR2	2.41	.57	-2.83	-.63	-1.20	-.25	-1.44	-.25	-.32	-.05	2.73	.37
IAR3	7.15	1.86	-6.77*	-2.05	-7.14*	-2.26	-.01	.00	2.38	.78	4.77	.97
IAR4	-1.70	-.36	-4.30	-1.07	-6.02	-1.37	-12.76**	-2.88	.57	.12	-2.27	-.34
IAR5	5.30	1.00	-9.21	-1.32	-12.07	-1.43	-23.03**	-3.18	2.45	.11	2.84	.13
IAR Spread	-3.20	-.45	15.18	1.39	15.90	1.11	11.19	.46	-17.48	-.45		

4-factor model, sorting *IAR* dependent on *IAV*

45 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	1.45	.51	4.70	1.46	4.57	1.19	-11.59	-1.56	-15.93	-1.35	17.38	1.43
IAR2	1.91	.34	-4.29	-1.04	-1.98	-.52	.03	.01	-.51	-.15	2.42	.37
IAR3	8.11	.89	-7.18	-1.00	-7.95	-1.31	1.33	.24	2.33	.52	5.78	.57
IAR4	-2.32	-.34	-4.35	-.85	-3.02	-.54	-12.35*	-2.28	.29	.05	-2.60	-.30
IAR5	5.48	1.38	-11.74*	-2.49	-10.83*	-2.08	-22.51**	-3.87	7.62	.50	-2.13	-.13
IAR Spread	-4.03	-.82	16.44**	2.88	15.40*	2.38	10.92	1.16	-23.55	-1.22		

4-factor model, sorting *IAR* dependent on *IAV*

50 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	3.12	.58	5.83	.62	6.12	.47	-18.09	-.70	-18.48	-.52	21.60	.60
IAR2	2.66	.56	-3.91	-.78	-5.89	-1.11	.23	.04	-.73	-.11	3.39	.41
IAR3	7.66	1.79	-7.31*	-1.98	-5.68	-1.61	1.50	.37	1.55	.46	6.11	1.12
IAR4	-3.33	-.63	-.74	-.16	-3.26	-.66	-11.29*	-2.28	-.33	-.06	-3.00	-.40
IAR5	4.90	.83	-10.79	-1.38	-7.88	-.84	-22.29**	-2.75	12.10	.50	-7.20	-.29
IAR Spread	-1.78	-.22	16.63	1.36	14.00	.88	4.20	.16	-30.58*	-1.98		

4-factor model, sorting *IAR* dependent on *IAV*

55 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	3.77	.67	5.61	.57	6.42	.47	-21.01	-.78	-18.28	-.49	22.05	.58
IAR2	3.08	.62	-3.28	-.62	-4.34	-.78	-.95	-.14	-.61	-.09	3.69	.43
IAR3	6.06	1.35	-6.65	-1.72	-4.85	-1.31	-.78	-.18	2.29	.64	3.77	.66
IAR4	-4.27	-.77	-.51	-.11	-2.39	-.46	-11.21*	-2.16	2.10	.38	-6.38	-.82
IAR5	6.70	1.08	-9.57	-1.17	-8.59	-.87	-23.07**	-2.71	12.53	.50	-5.83	-.22
IAR Spread	-2.93	-.35	15.17	1.18	15.00	.89	2.05	.07	-30.81*	-1.97		

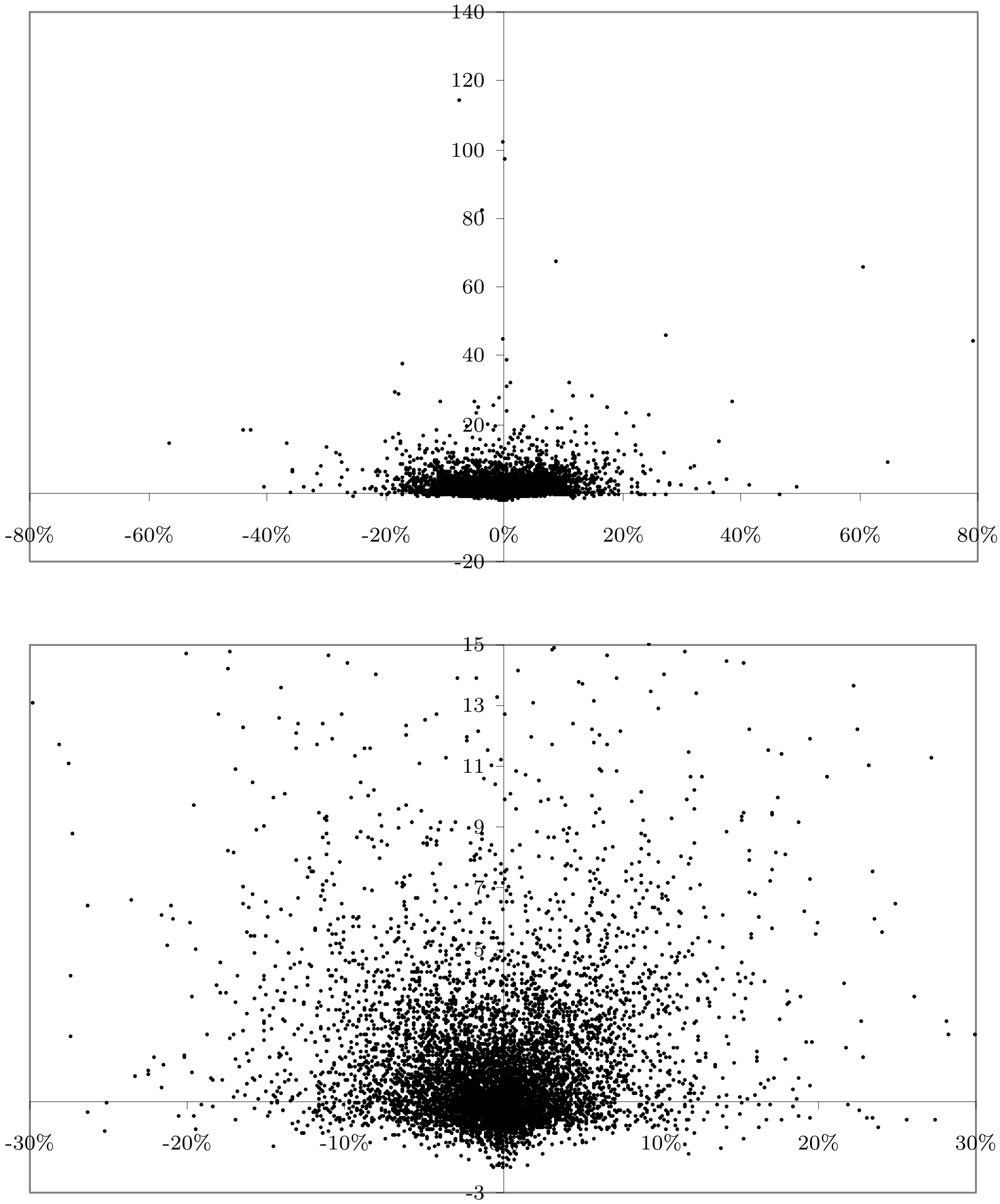
TABLE 13 (CONT.)

4-Factor Model, sorting *IAR* dependent on *IAV*

60 days	*IAV1*		*IAV2*		*IAV3*		*IAV4*		*IAV5*		*IAV* Spread	
	CAR	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*	*CAR*	*t*
IAR1	3.80	.65	4.81	.47	4.67	.33	-24.57	-.87	-16.19	-.41	19.99	.50
IAR2	3.42	.66	-1.62	-.29	-1.26	-.22	3.29	.47	-.54	-.07	3.96	.44
IAR3	5.56	1.18	-6.69	-1.65	-4.02	-1.04	-.76	-.17	6.68	1.79	-1.12	-.19
IAR4	-3.58	-.62	-.39	-.08	9.04	1.68	-9.25	-1.70	2.33	.41	-5.90	-.72
IAR5	8.81	1.36	-6.93	-.81	-10.96	-1.06	-25.21**	-2.84	13.30	.50	-4.49	-.17
IAR Spread	-5.02	-.57	11.74	.88	15.63	.89	.64	.02	-29.50	-1.30		

FIGURE 11 – IAR/IAV SCATTERPLOTS

Scatterplots depicting the correlation between the *IAR* (x-axis) and *IAV* (y-axis) metrics. The bottom plot is simply a close-up version of the upper plot.



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