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Earnings announcements and the Stockholm Stock Exchange: Irrational investors and market inefficiency

Bo W. Bergsten

Supervisor: Hans Jeppsson
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Abstract. Earlier research has demonstrated the existence of the anomaly post earnings announcement drift (PEAD) on several efficient markets; i.e. the phenomenon where an unexpectedly good (bad) earnings report causes a firms share price to outperform (underperform) the market for an extended time period after the report. Using event study methodology and an extended sample of 10,252 quarterly earnings reports from 297 small, medium and large-cap stocks listed on the Stockholm Stock Exchange during the time period 2005 through 2015, I confirm the existence of PEAD. I present a simple trading strategy that in theory would have generated 11.1 percent in annual abnormal returns. Using a more practical and perspicuous method, I confirm the findings of Setterberg (2007). My findings support the view that liquidity and risk factors are not the sole cause of PEAD and I argue for a behavioral explanation.

Acknowledgement

My partner, Emma. Your love, unlimited support and unprecedented patience has meant everything to me during my time as a graduate student.

My friend, Alex. A good friend makes you laugh, a great friend also makes you think.

My mom. Usually, only professional athletes enjoy such biased and loyal supporters.

Martin Holmén and Evert Carlsson. The education I received as a graduate student at HHG surpassed my expectations. Good work!

As this thesis ends my third university degree within the range of just four years it would be wrong not to mention my student counselor at primary school. At a compulsory meeting, she strenuously tried to coerce me into skipping high school and instead choose a practical education, like carpentry. At this juvenile age, I argued that in the future I might want to pursue a higher education and that I did not want to limit the opportunities for my future self. The student counselor concluded, with a lot of self-assurance and callousness, that I would never enroll in higher education as I was lacking “interest and motivation”…

Let this be a testament that we should never underestimate children; there is vast beauty in reaching ones potential, and a dark abyss in never getting the chance. To my juvenile self, although you are long gone, I am truly thankful for your providence and I forgive you for any supposed shortcomings you might have had.

Contents

1. Introduction

Post earnings announcement drift (PEAD) is the phenomenon where an unexpectedly good (bad) earnings report causes a firms share price outperform (underperform) the market for several days, weeks or months. Momentum is the phenomenon where past firm share price over-performers (under-performers) systematically keep on being over-performers (under-performers) in the future.

PEAD and momentum are interesting phenomena. First of all, they are violations of the efficient market hypothesis (Fama and French, 1996; Fama, 1998) – that share prices consistently represent the intrinsic value of the firm i.e. that it is impossible to systematically generate risk adjusted above market returns after taking account of transaction costs. Secondly, these phenomena could be open for exploitation by investors seeking to generate abnormal returns; i.e. risk adjusted returns that are higher than the market.

This thesis will take a new perspective on PEAD and utilize a method which combines both the firm specific information aspect of PEAD and the simplicity of momentum through the event study methodology outlined by MacKinlay (1997). Thus yielding results that highlight various aspects of market efficiency that is accessible, reliable and maybe even open for exploitation. Moreover, the thesis will offer specific information regarding the Stockholm Stock Exchange (SSE) and its potential efficiency or anomalies.

Instead of using statistical methods or analyst forecast of EPS - which is the current concord of researchers when assessing the *surprise* an earnings report yielded - I have used abnormal return on the first trading day after report (AROFT) as a base for analysis. This has several benefits. First of all, the AROFT is easily available for both private and public investors – minimizing risk for information asymmetry. Secondly, data on AROFT is easy to collect and have high reliability and validity in relation to forecasted EPS and statistical models. Thirdly, the AROFT will incorporate more information about the contents of the earnings report than a simple EPS forecast and we can safely assume that the AROFT on average will be driven by firm specific information.

In this study I construct three portfolios depending on their AROFT. All shares in the lowest decile in regards to AROFT constitute Portfolio 1. Those shares in the highest decile in regards to AROFT constitute Portfolio 10. I also constructed Portfolio Hedge, wish goes long in Portfolio 10 and short in Portfolio 1. Portfolio Hedge is the basis of my analysis - the trading strategy I am testing - and is commonly referred to as a *zero cost portfolio* as the long position is financed by the short (Setterberg, 2007). Moreover, the short position represents a reference point for the long position.

2. Background

2.1. PEAD

Ball and Brown (1968) proved the existence of post earnings announcement drift (PEAD), i.e. predicable abnormal stock returns after earnings announcements. When a firm presents an earnings announcement that beats expectations the share price is bound to increase instantly as a result, this is simply a result of markets acting efficiently (Fama, et al. 1969). However, the “drift-phenomenon” is the systematic effects where the share price keeps drifting in the same direction several days, or even months, after the earnings announcement is made (Kothari, 2001).

PEAD contradicts the efficient market hypothesis (Fama, 1998). If markets are operating in an efficient manner we expect that prices constantly will reflect underlying value, or put differently, that any mispricing cannot be used to systematically generate abnormal returns on a risk adjusted basis after taking account of transition costs.

Foster, Olsen and Shevlin (1984) showed that taking a long position in a stock at the highest decile of unexpected earnings and a short position stocks in the lowest decile in regards to unexpected earnings (below expectations) for the 60 subsequent trading days yielded annualized abnormal returns (alpha) of about 25 percent.

Ball and Brown (1968), Bernard and Thomas (1989, 1990), Freeman and Tse (1989), Mendenhall (1991), Wiggins (1991) and Bartov (1992) have all previously documented PEAD in various time periods and markets.

Using a statistical and long horizon model with constrained sample size, Hanna Setterberg (2007) showed the existence of PEAD and momentum on the SSE between 1990 unto 2005. Utilizing PEAD she constructed a trading strategy that generated an average return of 11 % a year. This return was robust to risk factors such as the Fama-French three-factor model (1993). This study will cover a later time period (2005-2015) and use a different model. Determining if PEAD still exists is interesting in itself and hopefully contrasting our models will also bring new inputs to the discourse.

The question researchers are asking themselves is why investors do not act upon the drift phenomenon; refusing to sell their shares for less than they could get if they just waited a few days, which would cause the share price to instantly after announcement reflect the intrinsic value instead of slowly drifting towards it.

2.2. Momentum

Jegadeesh and Titman (1993) was the first to show that buying shares that had performed well in the past and selling shares that had performed poorly was a strategy that generated risk adjusted abnormal returns. In more recent research Asness et al (2013) showed that so called *momentum* exists in a range of different asset classes. PEAD cannot be explained solely by momentum. They seem to be related but separate themes (Setterberg, 2007).

Interestingly, momentum strategies cannot be explained by risk factors (Bernard & Thomas, 1989; Chan et al., 1996; Grundy & Martin, 2001; Jegadeesh & Titman, 2001). Therefore, several behavioral factors have been put forth as explanations for momentum (Daniel et al. 1998) and lack of liquidity has also been suspected of contributing to momentum (Sadka, 2005) as well as information uncertainty (Francis, 2004).

All in all, it seems like markets responds to new information gradually (Chan et al., 1996). Share price momentum is considered as one of the biggest challenges to the efficient market hypothesis (Fama and French, 1996; Fama, 1998).

2.3. Structural and theoretical aspects of markets

2.3.1. Liquidity

According to the information efficiency framework, investors' active trading help bring prices toward their intrinsic value and mispricing is caused by lack of efficiency, which in turn is caused by transaction costs (Grossman and Stiglitz 1976, 1980). The mispricing is thereby coerced to be in line with the underlying transaction costs which the investors try to mitigate. In other words, the drift phenomenon could be explained by transaction costs that investors face, which inhibits them from taking advantage from the mispricing. The transaction costs in turn could be explained by, or compose, lack of liquidity in the market for that asset (Kyle, 1985).

Keynes (1930) defined liquidity as the ability to sell an asset on short notice without acquiring a loss. Generally, liquidity is seen as the ease of which an asset can be sold, i.e. how easily potential buyers and sellers can match and exchange. However, Keynes definition put emphasis on an important aspect of liquidity; that there exists a tradeoff for the seller between execution speed and settlement price. When several sellers enters a market, causing supply to increase, we expect the price to fall. The impact on the price will depend on the quantity of the asset entering the marketplace and continuity of trading in the market for that asset (Yamey, 1985). If the asset is traded very frequently, ceteris paribus, new sellers will have a smaller effect on the market price. In other words, volume of trading on the market could be seen as a measurement of liquidity. Therefore, volume of trading on the first trading day after report will be used as an estimate for liquidity in this study.

Market liquidity can also be assessed by the "tightness"; the width of the bid-ask-spread, where a small bid-ask-spread constitutes liquidity (Black, 1971). Hence, bid-ask-spread will be used as a measurement for liquidity in this study.

Some previous research suggests that illiquidity is the root cause of PEAD and that it mainly, or solely, appears in shares that are illiquid (Chordia et al., 2009; Sadka, 2006). Liquidity, or rather the lack of it, is widely regarded to have a connection with market anomalies.

2.3.2. Market Impact

Market prices are a result of supply and demand. Given a rise in demand, more buyers, we would expect prices to rise. The extent to which an investor changes the market price when she is in the process of buying or selling an asset is called market impact. The market impact always acts against the investor how tries to perform a trade and the effect will be more pronounced the more illiquid the market is (Kyle, 1985).

Perhaps PEAD is caused by large institutional investors who, as they take a position in a firm that has been beating expectations, have to dig deeper into the order book. This could explain the perseverance of the drift effect, institutional investors might want to exploit the effect but cannot due to the transaction cost associated with market impact i.e. they would end up causing the phenomenon that they want to utilize. Although limited liquidity might hinder institutional investors from exploiting the post earnings announcement drift, private investors might still be able to (individually, not on aggregate).

Drift is a form of inefficiency that, through the preceding argument, could be caused by professional investors as appose to private investors. This is rather counterintuitive, as private investors are sometimes blamed for market inefficiency (De Long et al., 1989).

If market impact is the cause of drift we would expect stocks that are less liquid to exhibit more drift. Alternately, (institutional) investors on average perfectly account for market impact costs - which would make less liquid stocks exhibit the same amount of drift as illiquid stocks.

When funds and institutional investors want to take a position in a firm that recently been beating expectations they reluctantly move the market by “depleting” the ask-side of the order book.

2.3.3. Risk factors

Market abnormalities - or phenomena that contradict the efficient market hypothesis – has often been contested on the grounds that the abnormalities in fact are just the market pricing assets according to their inherent risk. For example, the out performance of “value stocks” (Sharpe et al., 1993) and smaller firms (in regards to market cap) have been suggested, and largely acknowledge, to derive from their innate higher risk (Fama & French, 1992). Moreover, earnings surprise has been shown to have a strong relationship with value stocks (Porta et al., 1997)

However, several researchers has suggested that risk factors - such as Fama-French Three-Factor model - cannot explain drift and momentum (Bernard & Thomas, 1989; Chan et al., 1996; Grundy & Martin, 2001; and Jegadeesh & Titman, 2001; Setterberg, 2007).

2.4. Behavioral aspects of Markets

2.4.1. Rationality

Economic theory often assume that agents in markets are acting rational. Of course, most economists are aware of the existence of irrational behavior in traffic, at their own workplace, on Black Friday sales and even on the stock market. However, the irrational investors are usually dismissed as having little effect on prices as their behavior is either irrational in a symmetrical way (for every crazy bear there is an equally crazy bull) or because their behavior is exploited by rational arbitrageurs, which forces the prices back to “equilibrium”. Now chairman of the Federal Reserve Jannet Yellen and Economy Prize winner Akerlof (1985) concludes that a minority of irrational agents can affect the overall equilibrium in several markets. A theoretical cretic of the “rationality assumption” was also put forth by De Long et al. (1990).

2.4.2. Anchoring

In addition to the cognitive biases I have listed, the anchoring heuristic is of particular interest for this study. The anchoring effect is one of our most pronounced and robust cognitive biases (Furnham & Boo, 2011). During decision making and estimations, anchoring occurs when we let an initial piece of information have an excessive role in or assessment. Interestingly, anchoring can occur even if the initial information has no relevance for the current decision. For example, Tversky & Kahneman (1974) let participants of an experiment observe a roulette wheel (predetermined to stop at either 10 or 65) and afterwards guess the percentage of the United Nations that were African. The participants were clearly influenced in their assessment by what number they had been shown during the roulette wheel spin. As expected, anchoring also affects individuals during purchase-decisions (willingness to pay/accept) and is more pronounce during uncertainty about the desire to trade (Simonson & Drolet, 2004).

Given the anchoring effect’s strong influence on decisions, it is likely that investors are affected by it as well (Baker & Nofsinger, 2002). If investors while valuating a share are anchoring their decisions, we can assume that their anchor is the latest known share price. If this were to be true we can assume that investors will underreact to new information, such as an earnings report. Investors’ tendency to under react to news – such as an earnings report – has been shown by previous research (Barberis et al., 1998). If investors are influenced by the anchor effect we would expect share prices to drift and instead of adjust instantly.

2.4.3. Endowment Effect

In 1980 the “Father of behavioral economics”, Richard Thaler, presented the term endowment effect. The endowment effect is the psychological phenomenon that causes the subjective value of an object to increase once it is in the possession of a person. Formally, endowment is often measured as the difference between the willingness to pay and the willingness to accept a certain price to exchange a good, and has been known by psychologists since the sixties. The effect occurs instantly, even if the object is delivered at random and in spite of objective value, dismissing extortion and sentimentality explanations (Kahneman et al, 1990). The effect is unlikely to be the result of culture or learning as it is present even in apes (Kanngiesser, 2011) and young children (Harbaugh, 2001).

The endowment effect has significant implications for economic theory. The highly cherished Coase theorem states that the allocation of resources will be independent of the assignment of property rights as long as there are no transaction costs (Coase, 1960). The implication of this is that we would expect stock markets to be efficient as long as there are no transaction costs. However, the claims inherent in the Coase theorem are refuted by the endowment effect as the allocation of resources clearly will not be independent of the assignment of ownership rights (Kahneman et al, 1990) – the allocation will be skewed towards the incumbent owners of the assets.

How would the endowment effect affect investors? Once an investor has bought a stock the investor would value the company higher than previously, leading to an insipid reaction to negative news and higher subjective value. If we suppose that the endowment effect wavers off after negative news, we would expect the price of a share to decline slowly as investors start to act rationally, resulting in the drift phenomenon.

2.4.4. Prospect theory

Total rationality implies a linear relationship in choices between risk and reward, i.e. risk neutrality. Unsurprisingly, we expect people to be risk averse and hence show a concave relationship between risk and reward. Put differently, diminishing utility from increases in reward. The truth behind this intuition has been established for a long time (Kahneman & Tversky, 1984). However, people's decision-making in risky choices still left academics puzzled for a long time. For example, Friedman and Savage (1948) tried to discern the paradox that people choose a certain small loss in order to avoid an uncertain and unlikely big loss (insurance), while at the same time choosing an small certain loss in order to earn a highly unlikely big gain (lottery), their conclusion was that the utility function must include both convex and concave segments. However, what Friedman, Savage and contemporary thinkers failed to develop was the specific outline of the utility function that is now widely accepted.

In their seminal paper, Kahneman & Tversky (1979) showed that the utility function is concave in winnings and convex in losses and rooted in a subjective reference point. In other words, both the positive feeling of winnings and negative feeling from losses will be diminishing in regards to the change from the held reference point. Moreover, the pain from a loss is felt about twice as much as the joy from winning (Tversky & Kahneman, 1992).

The reference point is an important part of the prospect theory. First of all, it is subjective. The reference point could be your current state of wealth, but it could also be the state of wealth you expect to have (ibid). For example, if your grandparents give you $100 for your birthday it will feel like a loss if you expected $1000; even though your objective total wealth has increased. (As prominent psychologist Barry Schwartz once said: "the key to a happy life – low expectations".)

The convex utility function in losses has an important implication – people are risk seeking in losses. The fitting narrative is the agonized gambler at the casino who keeps increasing his betting size in order to "break even". The behavioral skewness towards risk taking will continue until the reference point has been moved (or reached). As Kahneman famously said: "A person who has not made peace with his losses is likely to accept gambles that would be unacceptable to him otherwise".

We can assume that the reference point of stock investors is the purchasing price (Weber & Camerer, 1998). Consider an investor who owns shares in a company which value just declined sharply after an unexpectedly bad earnings report. The prospect theory would imply that the investor would be reluctant to sell her shares, realizing a loss, and instead hold on to the shares in order to at least break even sometime in the future. This phenomenon is called the *disposition effect* and its existence and link to the prospect theory is well known (Shefrin & Statman, 1985). As the investor and her peers would be unwilling to sell their shares, the ask-side of the order book would be shallower than justified. However, it is possible that as the investors come to terms with reality, i.e. make peace with their losses, they will begin to sell their holdings one by one, causing the share price to go down not instantly, but slowly – generating the drift phenomenon (Frazzini, 2006).

Now consider the reverse situation, an investor owns shares in a company which value just increased due to a surprisingly positive earnings report. Although the investor might assume that the stock is still undervalued, the investor would be satisfied selling the share prematurely due to the concave and somewhat flat nature of the utility curve far from the reference point (Frazzini, 2006).

All in all, it is possible to argue that the drift phenomenon could be expected, or explained, by psychological factors outlined in the prospect theory.

2.5. Hypothesis development

In line with Setterberg (2007) I expect SSE to exhibit PEAD also for the time period 2005-2015. Also in line with Setterberg (2007), I expect the PEAD to be visible primarily on the upside. My sample, in opposition to Setterberg (2007) is unrestricted. As such, my data will enable comparisons between large and small cap firms, as well as between firms with high and low liquidity. Due to the behavioral factors listed, I expect drift to be present among both liquid and illiquid shares.

Hypothesis 1: PEAD on SSE for over performing firms i.e. an over performance of my long portfolio (Portfolio 10).

Hypothesis 2: PEAD on SSE for the zero cost Portfolio Hedge

3. Method

3.1. Sample

The sample consists of 10,252 firm-quarter-report observations, later referred to as events, from 297 firms listed on the Stockholm stock exchange (SSE) during the time period from January 2005 until December 2015. The total sample makes up 2,009,392 observations of share price returns, firm specific information and market returns. The sample includes small, mid and large-cap stocks. Due to unsound data, some observations during this time period was removed. Se appendix for more info regarding the sample.

3.2. Data

The data has been collected from Bloomberg's database. Daily dividend and split adjusted share price returns has been collected 120 trading days before each event and 60 trading days after.

A crucial piece of information is which date that is the first trading day (FTD) after report. Report date and time of report are easily available information. If the report was released after market close, the FTD was recorded as one day later, if that day was a holiday, then the date was postponed in the sample even further, and so on. For each event, various control factors has been collected for each firm for that specific time period; price-to-book (market capitalization divided by total equity on the FTD), market capitalization (closing price times number of shares), beta, alpha, total assets, total equity, debt, industry sector (GICS), volume traded, bid-ask spread and equity multiplier. All data regarding financial statements (such as total assets) has naturally been taken from the earnings report that the event represent.

I define volume traded as the sum of each transaction of the share on the FTD multiplied with the average price on the FTD. Average historical figures - both before and after the FTD - could be used of course. The pros and cons with the various ways to measure volume traded is not something I will dwell on here. However, I also compared this measurement of volume with a measurement that averaged volume traded over 10 trading days before the earnings report and the results were virtually identical (both for values regarding Portfolio 1 and 10 and for the resulting regression in section 4.2.4). In my study there is an underlying hypothesis that the share price movement on the FTD does not fully reflect the information in earnings report presented. Hence, it is the liquidity on the first trading day after report that I want to pin-point. Similarly, bid-ask spread is defined as the difference between the bid and ask price in the order book divided by the last trading price at market close on the FTD. Equity multiplier is calculated as the total assets divided by common equity and is therefore a measure of financial leverage. The GICS sectors “Energy” and “Utility” was merged as they had quite few observations.

3.3. Time-series predictions vs. Analyst forecast

Earlier researchers of PEAD has struggled with the problem of measuring to what extent an earnings report generated surprise. Their approach has generally been through two different ways. One way is to compare the results of the reports with that of analysts’ forecasts. The other way is by historical data statistically generate a trend of firms’ results and then comparing the statistically predicted results with the actual result of the firm. Collins and Hopwood (1980) and Brown and Rozeff (1978) concluded that analyst forecast generates more accurate forecast of earnings than the time-series statistical models presented by Brown and Kennelly (1972) and Foster (1977). This conclusion has also been underscored by Conroy and Harris (1987) and others. This might not be that surprising as we would expect analyst to utilize both statistical model and actual knowledge and understanding about the companies and the markets they operate in. This is the main reason why this study will not use the time-series predictions proposed by Foster (1977) and others.

3.4. Analyst forecast

Investors in stock markets pay attention to professional security analysts' opinions. We know this as analysts' earnings forecasts and revisions has a clear and significant influence on share prices (Brown et al., 1985). Therefore, using analyst forecasts to estimated market surprise makes some sense. However, analyst forecast as an approximation for earnings surprise has several drawbacks as well. First of all, collecting historical analyst forecasts is cumbersome. The way researchers quantify analyst forecasts, perhaps the only feasible approach available, is usually through earnings per share. However, the bottom line is only one aspect of a quarterly report. In regards to future cash flow generation and the firms' valuation it is often other information in the earnings reports that holds the biggest weight in investors' eyes. In other words, a significant part of share price movements due to surprises in the quarterly reports are caused by other factors than the net income (Hoskins et al. 1986, Francis et al. 2002). Moreover, which analysts' forecast should be use, and how could we know that they are in line with that of the market? After all, analysts might have other incentives than being right (Hilary & Hsu, 2013) or might simply fail to be right due to biases and other factors (Das et al., 1998; Fanelli et al., 2009). If we are interested in measuring the surprise effect of an earnings report, it could be argued that the difference between analysts' expectation of performance and actual performance lacks validity.

3.5. Stock market movement as approximation for surprise

I believe that the abnormal return on the first trading day after a report (AROFT) is a robust measure of how much surprise a quarterly earnings report generated. Assuming that investors has an interest in maximizing their profits we would expect them to try to predict quarterly results, the share price one day before the quarterly report would hence be the aggregate of that prediction (Fama, 1965). Moreover, the share price would also incorporate all aspects of a company's performance (Zhou et al, 2012), not just the very particular factors that are included in the statistical model or for that matter the numerous biases and incentives conceited in various analysts' expected earnings per share.

One arguable drawback of approximating surprise through share price movement is that it could generate somewhat of a logical loop; are we debunking the efficient market hypothesis with one hand and then using its supposed truthfulness with the other hand in order to prove a point. Naturally, this argument has little bearing; although we expect investors to try to be right, we might not expect them to succeed. Systematically the share price one day before report will tend to be the aggregate of investors' expectations (Fama, 1965). It is the opinion of the author that the academic community's stringent focus on poorly working time-series prediction and unsophisticated and oversimplified analyst forecasts is a weakness in asset pricing research.

3.6. Event studies

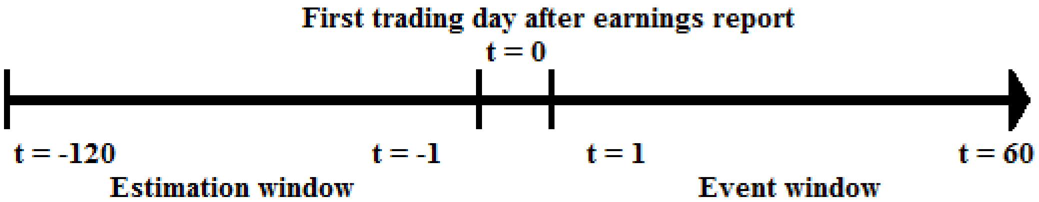
This thesis is based on event study. An Event study is a statistical method to evaluate the effect of an event on the share price of a firm. In this thesis the particular events we are studying is the quarterly reports the listed firms publish. The general approach to perform an event study, which is the foundation of this thesis, is explained by MacKinlay (1997). As financial markets are occupied by profit maximizing investors, we can expect that prices will adjust immediately to publicly available information of an event (ibid).

Event studies are divided into long-horizon event studies ranging from several months to several years, and short-horizon event studies ranging a few days to a couple of months (Kothari, 2001). In relation to short-horizon events studies, long-horizon event studies have been shown to have several issues and questionable reliability (Kothari & Warner, 2004; Kothari, 2001; Chen, 2014). This is one of the reasons why this thesis is based on a short-term horizon.

When performing an event study normal stock returns for each firm is assessed based on an estimation window prior to the event in question. In this study the estimation window is 120 days. Subsequently, the estimated "normal return" is deducted from the actual return on the event day. The resulting residual is the "abnormal return" which is expected to be caused by the event of study.

This analysis is based on an estimation window that occurs 120 trading days before the FTD (t = -120) until the last trading day before report (t = -1). Although there does not exist a *perfect* length for the estimation window, there is a consensus that 120 days is an appropriate length (MacKinley, 1997). Then, the AROFT (abnormal return on first trading day after report) is calculated for the first trading day after or at the earnings report (t = 0). Then an analysis is done on the event window, from the second day after earnings report (t = 1) (or first day after report if report was released before market closing) until 61 days after earnings report (t = 60) (or 60 days after report if report was released before market closing).

Figure 1



The above figure gives a visual explanation of how the estimation window, first trading day after earnings report and event window are related.

When calculating the normal return the following calculation is done on the estimation window.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t}$$

Where R is the return for stock *i* and market portfolio *m* at time *t*, α is the intercept and β is the linear relationship between the return of the stock and the return of the market. ϵ is the error term with mean zero.

$$\hat{\sigma}^2_{\epsilon_i} = \frac{1}{EW - 2} \sum_{t=-120}^{t=-1} \left(R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t}\right)^2$$

The estimated variance of the error term ϵ for security i is $\hat{\sigma}^2_{\epsilon_i}$. EW is the estimation window in days, i.e. 120.

Subsequently, the following calculation is performed on the event date in order to receive the AROFT.

$$AROFT_i = R_{i,t=0} - \hat{\alpha}_i - \hat{\beta}_i R_{m,t=0}$$

Where AROFT represent the abnormal return on first trading day after report for stock *i* at time *t* and $\hat{\alpha}$ and $\hat{\beta}$ is the alpha and beta calculated from the estimation period prior to the event.

Then, the abnormal return is calculated for each stock for the following investigation period of 60 days (event window).

$$AR_{it} = R_{i,t} - \hat{\alpha}_i - \hat{\beta}_i R_{mt}$$

Where AR represent the abnormal return for stock *i* at time *t* and $\hat{\alpha}$ and $\hat{\beta}$ is the alpha and beta calculated from the estimation period prior to the event.

The cumulative abnormal return (CAR) is calculated as the sum of abnormal returns that occurs from the second trading day after report (t = 1) unto a total event window of sixty days (t = 60).

$$CAR_i(t_1, t_{60}) = \sum_{t=1}^{t=60} AR_{i,t}$$

$$CAR_i(t_1, t_{60}) \sim N\left(0, \sigma_i^2(t_1, t_{60})\right)$$

The variance of CAR_i is calculated using the length of the event window (60) and the variance of the error term.

$$\sigma_i^2(t_1, t_{60}) = (60 + 1)\hat{\sigma}_{\epsilon_i}^2$$

The events are then sorted by their AROFT and subsequently divided into 10 portfolios with regards to their ranking; i.e. the events in the lowest decile of AROFT forms portfolio 1 and the events with the highest decile of AROFT shares forms portfolio 10.

Then, the cumulative average abnormal return (CAAR) is calculated for each portfolio *p*. Where *n* is the number of events in each portfolio.

$$CAAR_p(t_1, t_{60}) = \frac{1}{n}\sum_{i=1}^{n} CAR_i\,(t_1, t_{60})$$

The variance of the cumulative average abnormal return for portfolio *p* is

$$var\left(CAAR_p(t_1, t_{60})\right) = \frac{1}{n^2}\sum_{i=1}^{n} \sigma_i^2\,(t_1, t_{60})$$

Where *n* is the number of events (1025) *i* in each portfolio.

Inference is drawn using

$$CAAR_p(t_1, t_{60}) \sim N\left(0, var\left(CAAR_p(t_1, t_{60})\right)\right)$$

To test the hypothesis that abnormal returns are zero.

In order to test if the CAAR has a difference from zero that is statistically significant, H_0 can be tested using

$$\theta_1 = \frac{CAAR_p(t_1,t_{60})}{var\left(CAAR_p(t_1,t_{60})\right)^{\frac{1}{2}}} \sim N(0,1)$$

Naturally, there could be other factors than the particular event that affects the share price on the first trading day after report. However, as several hundred events are merged in the model we expect that the various disturbance factors will be smudged as they are hopefully uncorrelated. There is a possibility that the “disturbance factors” are not mere white noise but the result of underlying forces at work. Unsurprisingly, an objective in performing event studies is to try to control for such factors.

3.7. Portfolio regression

In order to test the predictability of various control factors I performed a regression analysis on the total sample with the CAAR after 30 days (of trading after earnings report release) being the dependent variable. The independent variables were AROFT, volume traded, bid-ask-spread, market capitalization, market-to-book and equity multiplier. Additionally, dummy variables for industry-sectors were included. Telecommunication services was chosen as the reference sector as it had the smallest absolute CAAR after 30 days of trading. The regression was performed with White’s robust standard errors.

The following regression was performed where α is the intercept, β-values represent regular control variables, δ-values represent dummy variables and ε is the conventional error-term.

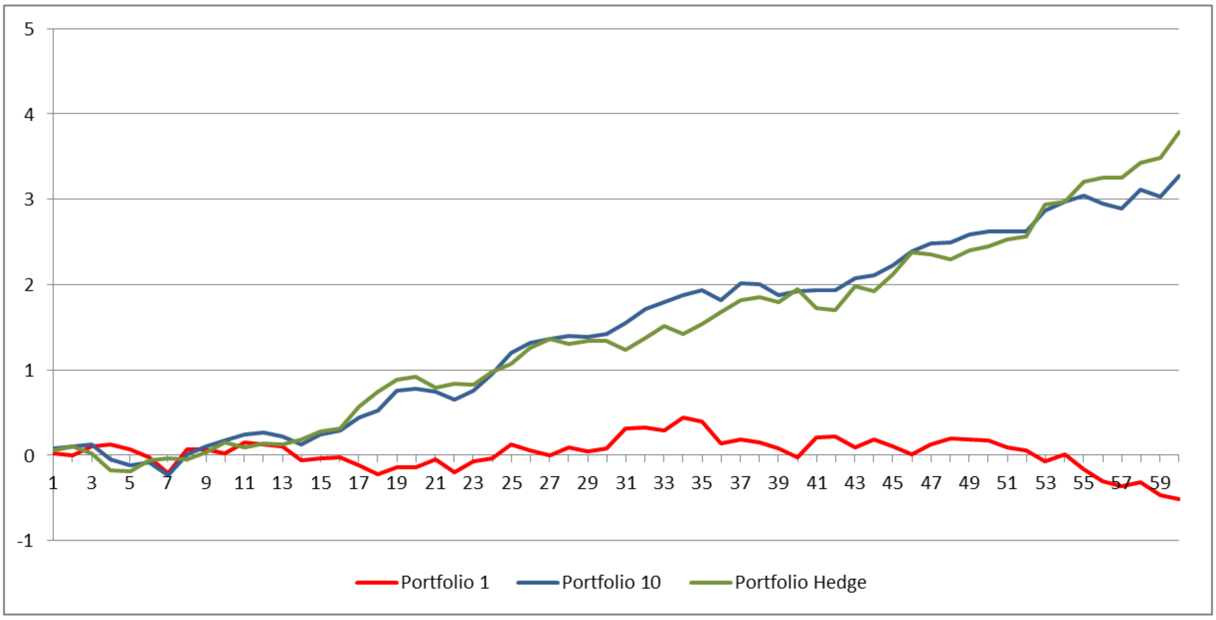
$$\begin{aligned} CAAR_{30\,days} = {} & \alpha + \beta_1 AROFT + \beta_2 Volume\ traded + \beta_3 Spread + \beta_4 MCAP \\ & + \beta_5 Market\ to\ Book + \beta_6 Equity\ Multiplier + \delta_1 Energy\ \&\ Utility \\ & + \delta_2 Materials + \delta_3 Industrials + \delta_4 Consumer\ Discretionary \\ & + \delta_5 Consumer\ staples + \delta_6 Health\ care + \delta_7 IT + \varepsilon \end{aligned}$$

4. Results

4.1. Performance

In figure 2 the returns of the constructed portfolios are presented over a 60 trading days holding period.

Figure 2 – Portfolio Returns (CAAR)



Development of Portfolio 1 (lowest decile of AROFT), Portfolio 10 (highest decile of AROFT) and Portfolio Hedge (long in Portfolio 10 and short in Portfolio 1) aggregated over a 60 trading days holding period for the total sample. The vertical axis shows CAAR in percentage and the horizontal axis shows trading days after FTD.

Portfolio 1, composing of shares from the events with the lowest decile in AROFT, had a CAAR of 0.08 percent and -0.51 percent after 30 and 60 trading days respectively. None of these values were statistically different from zero.

Portfolio 10, composing of shares from the events with the highest decile in AROFT, had a CAAR of 1.42 percent and 3.28 percent after 30 and 60 trading days respectively. Both these values had a difference from zero that were statistically significant.

Portfolio "Hedge", generated by going long in portfolio 10 and short in portfolio 1, had a CAAR after 30 trading days of 1.33 percent and a CAAR after 60 trading days of 3.79 percent. Both these figures are statistically significant.

There is a general critique against extensive event windows, as other later occurred factors might distort the effects of the *event* you are trying to study. Hence, it is sensible to take higher regards of the 30 days CAAR than the 60 days CAAR. A hypothetical investor that followed the proposed investment strategy would have been expected to outperform the market by approximately 11.1 percent a year (given 250 trading days a year and the 30 days CAAR). If we take into account the average bid-ask spread (0.139 %) and brokerage fee (0.25 %[1]) and assume a holding period of 60 days; then the investor would have yielded average yearly abnormal returns of around 9.5 percent after including transaction costs. Obviously, this assumes that the investor is a private investor holding a limited portfolio with no limits to short-selling. As one can easily deduce, similar results would be obtained if the investor choose not to short-sell portfolio 1. Worth mentioning, the *cut-off* for what AROFT that is to constitute a share for Portfolio 1 or 10 is an ex post invention (after the time period studied has already occurred), while the investment has to be made before the exact cut-off figures are actually known. The cut-off limit for Portfolio 1 was an AROFT of below -6.2708 % and the cut-off for Portfolio 10 was and AROFT above 6.3228 %.

Table 1 – Portfolio characteristics

	Portfolio 1	Portfolio 10	Portfolio Hedge
30 DAYS STD(CAAR)	0,5795	0,4960	0,3814
60 DAYS STD(CAAR)	0,8063	0,6901	0,5306
30 DAYS P-value	0,4429	0,0021	0,0002
60 DAYS P-value	0,2633	0,0000	0,0000
30 DAYS CAAR	0,0833	1,4201	1,3368
60 DAYS CAAR	-0,5105	3,2775	3,7880

Standard deviation, p-value and CAAR for the 3 portfolios.

[1] Price taken from Avanza, Sweden's largest online stock broker, April 2016. The brokerage fee chosen for the calculation is the most expensive one they offer, aimed at private investors with small portfolios. www.avanza.se

4.2. Robustness

With the event study methodology it is not feasible to make statistical inference regarding various control factors. Hence, in order to illuminate the effects regarding alternative explanations to my findings, I will go through them one by one in a descriptive sense. Insights can be drawn in this manner which will simplify for potential future researchers in this field. In section 4.2.4 present results from a regression analysis that will further discern the role of different factors and their effects on PEAD.

As the CAAR of Portfolio 1 was not statistically different from zero, the comparisons will focus on portfolio 10.

4.2.1. Liquidity

Previous researchers has suggested that liquidity might the root cause of drift and momentum (Chordia et al., 2009). In regards to bid-ask-spread, the average for all events in the sample was 0.125 %. Portfolio 10 had a lower bid-ask-spread on average (0.121%), although not statistically different from the full sample.

In regards to volume trading on FTD. The results go in line with that of bid-ask-spread. Portfolio 10 and Portfolio 1 had higher liquidity in this regard.

Within Portfolio 10, there were no correlation between the drift (CAAR) and spread (0.05) nor volume traded (-0.03). For the total sample the same relationship holds; the correlation is miniscule between CAAR, spread (-0.002), volume traded (0.008) and market capitalization (-0.018).

If some underlying factor besides unambiguous market inefficiency is driving the results I have shown in this study, it seems unlikely that this factor is liquidity.

4.2.2. Sectors

None of the industry sectors (GICS) had an average AROFT, 30 days CAAR or 60 days CAAR that was statistically different from the total population. The three sectors that had noticeably larger 60 days CAAR was Health Care (1.33%), Consumer staples (-1.21%) IT (0.50%). Amongst these Portfolio 10 had an underrepresentation of IT (12% against 15%) and Industrials (16% against 19%) and a slight overrepresentation of Health Care (7% against 6%).

Generating a hedge portfolio - in the same way as previously - divided by each industry sector showed some interesting results. Information Technology sector had a cumulative abnormal return after 60 trading days of 8.5 %, Consumer Discretion 6.0 % and Telecommunication 4.3%. The other sectors had a CAAR that was below the average for the total sample. Portfolio 10 has an overrepresentation of Consumer discretion (22 % against 19 %) and Telecommunications (4 % against 3 %). However, as previously mentioned, a clear underrepresentation of the most extreme sector IT (12% against 15%). See appendix for more info regarding sectors.

4.2.3. Risk factors and valuation

As previous researchers has rejected the notion of risk factors as the driving cause of drift, it makes little sense to dwell on this topic. In regards to market-to-book valuation - which can be used as an approximation for how risky a firm is viewed by the market - Portfolio 1 and 10 has higher valuation than the total sample. Moreover, there were virtually no correlation between CAAR and market-to-book (0.018). The “value effect” is thus an unlikely origin for the higher CAAR of Portfolio 10.

The average event in Portfolio 1 and 10 also had smaller market capitalization, but to a much lesser extent. This suggests that the “small-minus-big”-effect might be driving the results presented. It could be that the low market capitalization firms are harder to trade outside of the market, through brokers and dark pools etc. If it were so then perhaps shares liquidity is overstated by the measures chosen in this study (volume traded and spread). This could implicate that the stock-specific liquidity is in fact the driving cause behind drift.

In regards to leverage, the equity multiplier equity multiplier was significantly lower for Portfolio 1 (1.74) and Portfolio 10 (1.64) than the total sample (2.38).

4.2.4. Portfolio regression

In order to disentangle the effects of various control factors I performed a regression analysis with the 30 days CAAR being the dependent variable. AROFT, volume traded, spread, market capitalization, market-to-book, equity multiplier being independent variables along with industry-sector dummy variables. Telecommunication services, due to its limited 30 days CAAR served as the “base-sector” and is thus not included as a dummy. White’s robust standard errors were used in order to account for any problems with heteroscedasticity.

Table 2 – Regression of 30 days CAAR

Number of obs = 10,252						
F(14, 10237) = 1.54	R-squared = 0.0023					
Prob > F = 0.0870	Root MSE = 13.251					
CAAR - 30 days	Coef.	Robust Std. Err.	t	P>t	[95% Conf. Interval]	
AROFT	.0779502	.0304176	2.56	0.010	.0183257	.1375747
Volume	4.56e-09	1.76e-08	0.26	0.795	-2.99e-08	3.90e-08
Spread	8.744424	8.758012	1.00	0.318	-8.422993	25.91184
Market Cap	-2.70e-06	1.53e-06	-1.77	0.076	-5.70e-06	2.87e-07
Market-to-book	-.007819	.0168624	-0.46	0.643	-.0408725	.0252346
Equity multiplier	.0647481	.0673556	0.96	0.336	-.0672822	.1967783
Energy & utility	-2.146203	1.101885	-1.95	0.051	-4.306114	.0137074
Materials	-.1118564	.7371793	-0.15	0.879	-1.556872	1.333159
Consumer discretionary	-.3922619	.6341992	-0.62	0.536	-1.635417	.8508928
Consumer staples	-.9023617	.7576642	-1.19	0.234	-2.387532	.5828085
Healthcare	.1528425	.7381117	0.21	0.836	-1.294001	1.599686
Financials	-.1495292	.6505958	-0.23	0.818	-1.424824	1.125766
IT	.1619284	.668218	0.24	0.809	-1.14791	1.471766
Industrials	-.3267335	.6056936	-0.54	0.590	-1.514012	.8605446
_cons	.1134309	.5813458	0.20	0.845	-1.026121	1.252982

This table includes the regression results of a regression on the total sample studied. The dependent variable is the CAAR generated after 30 trading days after earnings report being released. The independent variables are AROFT, volume traded, bid-ask-spread, market capitalization, market-to-book, equity multiplier and dummy variables for industry-sectors (with *telecommunication services* being the reference sector). The regression is performed with White's robust standard errors.

The regression result in large support my previous conclusions. Risk factors, such as market to book and equity multiplier does not seem to play a part in PEAD. The same is true for industry sectors (although Energy & Utility is significant at the 10% level of confidence). AROFT is the only variable included that seem to have explanatory power for the 30 days CAAR.

In this regression, market capitalization is statistically significant at the 10% level. Naturally, market capitalization is closely correlate with volume traded. When volume traded is excluded from the regression then market capitalization is indeed a statistically significant explanatory variable. This raises the question of whether market capitalization is a better approximation for liquidity, and if liquidity is indeed what causes PEAD. First of all, no matter what variables that is excluded, spread and volume traded never becomes statistically significant explanatory variables. However, it could still be that market capitalization characterize off-market liquidity (broker-trading, dark-pools etc) and on-market liquidity that is simply not covered by the other explanatory variable (volume traded and spread). Conversely, market capitalization might imply other underlying factors that generate PEAD, such as risk and attention. Perhaps the media and investors are less attentive to shares that have low market capitalization which could cause the share price to adapt slowly to new information. Moreover, the fact that market capitalization is a significant explanatory variable could be because of the classical *"small minus big"-effect*, i.e. the known tendency for small market capitalization stocks to outperform the market. However, the bottom line is that even if we control for all three measures of liquidity - market capitalization, bid-ask-spread and volume traded - AROFT is still a statistically significant explanatory variable, i.e. the proposed trading strategy generates abnormal returns even if we control for liquidity.

5. Discussion

Investing in firms that have outperformed their expectations seems to be a sound investment strategy. In regards to the method used in this study, and its limitations, both hypothesis 1 and 2 are confirmed; the trading strategy used for Portfolio 1 and Portfolio Hedge generate abnormal returns. This study highlights that there exists several market anomalies that cannot easily be explained away by inherent factors. The drift abnormality has been recognized for a long time, yet it is still present on the SSE. This is significant as the SSE is considered a developed and efficient market by international standards.

The drift effect is present to a much larger extent on the upside than on the downside. This is in line with Setterberg (2007), which underscores the robustness of the method applied in this study and confirms her findings. Moreover, PEAD is present to a similar extent using my method; yearly abnormal returns of approximately 11 percent. If we assumed that the leading cause of drift was behavioral factors, such as the prospect theory, we might have guessed that drift would be equally or even more present on the downside. People experience pain stronger than joy and are subject to the endowment effect etc., as such, if drift is caused by these factors it would manifest on the downside. Nonetheless, structural factors, such as liquidity, does not seem like a plausible explanation either. If it were so that institutional investors created drift by “depleting” the ask-side of the order book when they wanted to invest in a firm that have been beating expectations; we would expect there to be a strong relationship between the CAAR from events with high AROFT and their liquidity. However, there exists no such relationship, not even a suggestion of a relationship. Moreover, Portfolio 10 as a whole had a higher liquidity on average that the total sample.
It thus seems likely then that behavioral factors are in play after all. The diminishing psychological return from increases in wealth could explain the upside drift. The greater the

gain the more risk averse one becomes according to the prospect theory. It is likely then that investors sell their holdings early after a sharp gain in order not to risk losing that gain. Moreover, the “anchoring effect” could explain investors’ tendency to consider the latest trading price and then from that price revising their assessment with to small adjustments.

This study seems to dismiss market impact, and in turn liquidity, as the causal explanation of drift and its consequential market inefficiency. However, an alternative explanation is that investors *perfectly account* for the lack of liquidity and the resulting market impact; causing the realized drift to be identical and independent from actual liquidity. Moreover, perhaps the Portfolio 10 shares are in fact less liquid, although they do not appear so when only using measurements of the SSE i.e. they could be illiquid on off-market trading (through broker-trading and dark pools etc). This could be an implication of the fact that the firms in Portfolio 10 had lower market capitalization on average. These are areas of suggestion for future research in order to disentangle structural aspects of markets from behavioral aspects. It is probable that they both play a part. Structural aspect we can change, but in the end it might be impossible - even for profit maximizing investors - to act truly rational.

It is important here to note that my study does not in any way *prove* that behavioral factors are the causal generator of PEAD. By way of abduction I wish to show and highlight that it is a *likely* contributor to PEAD; in order to steer future research in this direction.

If SSE is truly efficient, and it is impossible to consistently generate above market returns after taking account for transaction costs, then this might be contingent on investors’ inability to rid themselves of their inherent biases and cognitive shortcomings.

6. Appendix

Table 3. Sample characteristics

	Market		Portfolio 1		Portfolio 10	
	Average	Std	Average	Std	Average	Std
Market CAP MSEK	27 918	70 256	22 463	70 117	20 962	59 947
Market-to-Book	3,39	3,54	3,75	3,61	3,48	9,28
Volume MSEK	2,117	7,506	3,474	11,021	3,417	12,410
Bid-ask-spread	0,12%	0,19%	0,16%	0,24%	0,12%	0,19%
DEBT-TO-MCAP	0,70	1,91	0,62	1,92	0,51	1,52
Equity multiplier	2.38		1.74		1.64	
CAAR - 30 days	0,049	13,264	0,083	18,581	1,420	14,264
CAAR - 60 days	0,093	17,827	-0,510	22,651	3,277	19,626

Table 4. Sectors.

	GICS	AROFT	CAAR 30	CAAR 60
10 & 55	Energy & Utility	-0,21	-1,88	0,15
15	Materials	0,02	0,15	-0,25
20	Industrials	0,10	-0,10	-0,04
25	Consumer Discretionary	0,11	-0,14	-0,39
30	Consumer Staples	0,16	-0,63	-1,21
35	Health Care	-0,41	0,34	1,33
40	Financials	0,04	0,20	-0,20
45	Information Technology	-0,18	0,43	0,50
50	Telecommunication Services	-0,16	0,04	0,20

Table 5. Sectors continued.

GICS	DECILE 1 AROFT	Decile 1 CAAR 30	Decile 1 CAAR 60	DECILE 10 AROFT	Decile 10 CAAR 30	Decile 10 CAAR 60	Hedge CAAR 30	Hedge CAAR 60
Energy & Utility	-5,09	-5,41	2,37	4,53	-1,71	2,01	3,71	-0,36
Materials	-5,42	4,12	2,08	5,73	-0,01	2,05	-4,14	-0,03
Industrials	-6,44	-0,52	-1,16	6,46	1,68	0,83	2,20	1,99
Consumer Discretionary	-6,83	-0,04	-2,30	7,56	2,35	3,74	2,38	6,04
Consumer Staples	-5,51	-1,41	-1,03	6,06	-0,95	0,36	0,46	1,39
Health Care	-6,71	2,74	1,68	6,30	1,83	3,90	-0,91	2,22
Financials	-3,54	0,74	-1,51	3,83	-0,19	1,04	-0,93	2,55
Information Technology	-7,39	-2,01	-2,65	6,65	2,87	5,85	4,88	8,50
Telecommunication Services	-7,99	-0,97	-0,70	7,98	-0,19	3,59	0,78	4,29

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