Pursue Uncertainty, But Skip the Dip

Information Uncertainty, Investor Sentiment, and the Post-Earnings-Announcement Drift in Sweden

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ABSTRACT

This thesis investigates the post-earnings-announcement drift (PEAD) in Sweden during 2005-2023, using event-time and calendar-time analysis. It further examines whether the magnitude of the drift is associated with information uncertainty and investor sentiment. Adopting the behavioral view that PEAD stems from investor underreaction, we hypothesize that firms with higher uncertainty exhibit more drift, and that the drift is associated with the prevailing investor sentiment. We find evidence of PEAD and show that the drift is stronger for high-uncertainty firms, and weaker during periods of low investor sentiment. From this, we propose a selective trading strategy that outperforms the standard PEAD strategy and generates gross monthly abnormal returns of 1.23% (15.8% annualized) after controlling for market, size, value, and momentum as risk factors. However, the net abnormal return is sensitive to trading frictions, suggesting that the Swedish market is more efficient than implied by gross PEAD returns.

Keywords: post-earnings-announcement drift, information uncertainty, investor sentiment, behavioral finance

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1. Introduction

Post-earnings-announcement drift (hereafter, PEAD) is a market anomaly in which stock prices underreact to earnings surprises and subsequently drift to incorporate the full information content of the announcement. This phenomenon creates a predictable return pattern which challenges the Efficient Market Hypothesis (EMH), and may be financially exploited by investors.

We view the origins of the anomaly through the lens of behavioral finance and investigate the impact of information uncertainty and investor sentiment on PEAD in the Swedish market. Specifically, we hypothesize that a higher level of information uncertainty will cause a greater underreaction to earnings surprises and consequently exhibit more drift, and that the prevailing market sentiment will influence the level of behavioral biases and thus the magnitude of PEAD. Accordingly, our analysis focuses on three dimensions: (i) the magnitude of earnings surprises, (ii) the level of uncertainty in the information signal of the earnings surprise, and (iii) the prevailing investor sentiment. Accordingly, the central research question guiding our thesis is: Does firm-specific information uncertainty and the prevailing investor sentiment influence the magnitude of PEAD in Sweden?

Combining price data from FinBas at the Swedish House of Finance Research Data Center, earnings announcement data from the Institutional Brokers Estimate System (IBES), and investor sentiment data from the Baker-Wurgler Sentiment Index, our sample consists of quarterly earnings announcements for equities listed on the Stockholm Stock Exchange from 2005Q1 to 2023Q1. We use two complementary methodologies to examine PEAD. First, we conduct an event-time analysis based on Cumulative Abnormal Returns (CARs) to capture price reactions post earnings announcements. Second, we apply a calendar-time portfolio regression approach to estimate the risk-adjusted monthly abnormal returns of a PEAD-based trading strategy. Together, these methods provide information about the timing of the anomaly and the possibility of trading on it.

We draw five main conclusions. First, the event-time and calendar-time analyses confirm the presence of PEAD in the Swedish market during our sample period. Second, under both methodologies, stocks with higher information uncertainty generate significantly higher abnormal returns compared to those with lower uncertainty. Third, for both methodologies, we find that PEAD in Sweden is concentrated to smaller firms. Fourth, the calendar-time analysis reveals that the performance of the PEAD strategy diminishes during periods of low sentiment. Fifth, based on our findings, we construct a selective PEAD-based trading strategy that focuses exclusively on high-uncertainty stocks and avoids low-sentiment periods. This strategy outperforms the standard PEAD approach, earning monthly abnormal returns of 1.23% (15.8% annualized) after controlling for market, size, value, and momentum as risk factors. However, the net profitability is sensitive to transaction costs and borrowing fees, potentially exposing the persistence of the drift to be a result of trading frictions. Our results are robust across alternative proxies for earnings surprises, information uncertainty, risk factors, and other variations of critical assumptions.

Our thesis extends and contributes to the body of literature related to PEAD by (i) increasing the sample period to assess whether PEAD remains observable in the Swedish stock market, (ii) investigating whether information uncertainty is associated with PEAD in the Swedish market, (iii) investigating whether PEAD in the Swedish market is related to investor sentiment, (iv) varying the empirical methodology relative to previous literature, and (v) providing a normative recommendation for how an investor may increase PEAD returns based on the information uncertainty in earnings signals and the prevailing investor sentiment. Our findings are relevant both for academics exploring the limits of market efficiency, and to practitioners aiming to design informed trading strategies based on firm- and market-level conditions. More broadly, our study highlights the importance of incorporating behavioral insights into empirical asset pricing.

2. Related Literature and Hypothesis Development

2.1 The Efficient Market Hypothesis and Earnings

Research on how information is incorporated into financial markets traces back to Regnault (1863), who observes similarities between random sequences of numbers and market prices. This insight lays the foundation for the random walk hypothesis (Bachelier, 1900), which suggests that past price movements are not predictive of future returns (Fama, 1965). The idea is later formalized and expanded by Fama (1970) into the Efficient Market Hypothesis (EMH) with three forms: weak, semi-strong, and strong, each defined by the subset of information reflected in stock prices. Of particular relevance to this thesis is the semi-strong form, which posits that all publicly available information is immediately and fully incorporated into stock prices.

Of the public information available to investors, accounting information and specifically accounting earnings are especially important. Under ideal mark-to-market accounting, these should equal investors' return for a period, following the concept of economic income as defined by Hicks (1939). When such accounting conditions are not available, reported earnings may still be considered a signal of economic income, and one should therefore expect an empirical association between reported earnings and stock prices. Thus, earnings announcements test semi-strong market efficiency by providing new public information that is material for stock valuation. In relation to this association, Ball and Brown (1968) find evidence of how the stock market reacts to annual earnings announcements. First, they find that positive earnings surprises are linked to increases in stock prices, while negative earnings surprises lead to decreases. This supports the notion that accounting information in earnings announcements presents information relevant for the formation of stock prices. Second, they find that 85-90% of the reaction occurs before announcements, supporting the idea that markets are somewhat efficient in incorporating information available through more prompt sources than annual reports. Third, and most important for this thesis, they find that prices continue to drift in the direction of earnings surprises for months following announcements, suggesting that the immediate reaction to earnings news is incomplete.

2.2 The Post-Earnings-Announcement Drift

2.2.1 Empirical Foundations

Rendleman et al. (1982) is the first major study to formally identify PEAD as a persistent anomaly. Examining US stock returns in the years 1970-1980, they find that by sorting stocks on the level of earnings surprise, measured by Standardized Unexpected Earnings (SUE), abnormal returns can be generated in the three months following the announcement. Subsequently, Foster et al. (1984) provides the first evidence of the possibility of constructing an implementable trading strategy to exploit the anomaly while avoiding hindsight bias. They find that, by sorting portfolios on time-series-based earnings forecast errors, an investor may earn a 3.23% abnormal return by holding a portfolio of the most positive decile of earnings surprises and -3.08% on the most negative decile, over the 60 trading days following the earnings announcement, using only publicly available information from 1974-1981.

Bernard and Thomas (1989) expand these findings using data for NYSE/AMEX firms from 1974 to 1986. They calculate abnormal returns as raw returns minus the equally weighted average return of the corresponding size-decile market portfolio, and estimate SUE as the difference between actual and forecasted earnings, scaled by the standard deviation of forecast errors. Based on these definitions, firms are sorted into decile portfolios according to their SUE. The PEAD strategy, i.e., a long position in the portfolio with the highest earnings surprises and a short position in the portfolio with the lowest earnings surprises, generates an abnormal return of 4.2% over the 60 trading days following the earnings announcement, equivalent to approximately 18% on an annualized basis. Since then, a large body of research documents the PEAD anomaly across different markets, industries, and time periods, using differing methodologies (Fink, 2021).

2.2.2 Methodological Variations

A central component of PEAD research is the measurement of earnings surprises. The objective is to quantify the deviation between reported earnings and the market's ex ante expectations, thereby capturing the theoretical magnitude of new information to be assimilated into prices. Early studies often use time-series models, such as the seasonal random walk, to estimate market expectations (e.g., Foster et al. (1984); Bernard and Thomas (1989); Hew et al. (1996)). This approach assumes that earnings follow a predictable quarterly pattern based on historical data. Other studies infer earnings surprises from ex post abnormal returns around the announcement window, assuming that the immediate market reaction reflects the unexpected component (e.g., Chan et al. (1996); Brandt et al. (2008); Gerard (2012)). This method is said to capture not only the response to the earnings figure itself, but also to any other information disclosed concurrently. A third approach is to apply analyst consensus forecasts, using the earnings predictions of professional analysts as a proxy for market expectations (e.g., Abarbanell and Bernard (1992); Doyle et al. (2006); Livnat and Mendenhall (2006)). This approach benefits from incorporating forward-looking information, but may be biased by analysts' incentives and the limited coverage for smaller firms (Lim, 2001).

Studies on PEAD use various methods to measure abnormal returns, i.e., returns in excess of a benchmark. Early research primarily focuses on event-time portfolios, where returns are tracked in a window relative to each firm's earnings announcement. These studies typically measure cumulative abnormal returns (CAR) or buy-and-hold abnormal returns (BHAR) over different post-announcement holding periods (e.g., Rendleman et al. (1982); Foster et al. (1984); Bernard and Thomas (1989); Liu et al. (2004)). More recent studies often adopt a calendar-time approach, forming monthly portfolios and analyzing the drift using risk-adjusted portfolio regressions (e.g., Chan et al. (1996); Dische (2002); Francis et al. (2007); Forner and Sanabria (2010)). Despite methodological differences, empirical findings are mostly aligned over different markets and time periods.

2.2.3 Global Evidence

While early studies focus on US equities (e.g., Rendleman et al. (1982); Foster et al. (1984); Bernard and Thomas (1989)), subsequent studies analyze PEAD internationally. Griffin et al. (2010) investigate PEAD in 56 developed and emerging markets for the period 1994-2005. They find that high-minus-low PEAD portfolios generate an average six-month return of 4.1% in developed markets and 4.2% in emerging markets (8.5% annualized). Additionally, Hung et al. (2015) find PEAD to be statistically significant in 18 out of 30 markets over 2001-2004. However, for the period 2006-2009, this is reduced to 13 out of 30.

Several country-specific studies examine PEAD portfolios using calendar-time regressions. For the UK market, Liu et al. (2003) investigate the period 1988-1998 and find PEAD portfolios to generate statistically significant abnormal returns of 0.706% per month (8.8% annualized), after adjusting for Fama-French 3-factor (FF3) risk exposures. In the United States, Francis et al. (2007) study PEAD using data from 1982-2001. Their findings are consistent, reporting monthly abnormal returns of 0.68% (8.5% annualized) when controlling for the same FF3 model. In continental Europe, Forner et al. (2009) analyze the Spanish equity market and find monthly abnormal returns of 0.593% (7.4% annualized) over 1992-2003, again after controlling for FF3 risk factors. Ahlatcıoğlu and Okay (2021) study Turkish stocks in the years 2007-2018. After controlling for FF3 risk factors, they find that a portfolio formed based on analyst forecast SUE could earn 0.773% monthly abnormal returns (9.2% annualized).

While most studies have identified PEAD, there is also evidence of the contrary. For example, van Huffel et al. (1996) does not find it in Belgium. Furthermore, Martineau (2019) argues that the drift is not present for large US stocks (S&P 1500) in recent periods (2010-2015). Ali et al. (2020) also find the anomaly to be decreasing in the period 1990-2014.

To this date, few papers study PEAD in the Swedish stock market. To the best of our knowledge, the first paper to investigate PEAD in Sweden is Griffin et al. (2010), examining the degree of stock price information efficiency in 56 international markets between 1994-2005. The authors test for several market efficiency metrics, one being PEAD from earnings surprises. They use data from IBES and measure earnings surprises as the difference between actual earnings and the mean of the last forecast of each analyst covering the stock between 14 and 182 calendar days prior to the announcement, scaled by the stock price at 6 to 12 days prior to the event. Thereafter, the daily BHAR of the portfolio formed on a long position in the 60% most positive earnings surprises and short position in the 60% most negative earnings surprises are reported over the 6-month period following the announcement. While the results are solely presented graphically, they find evidence of PEAD of approximately 9% (19% annualized) in Sweden. Furthermore, in a working paper preceding the published version, Griffin et al. (2006) show that the drift in Sweden is primarily stemming from the negative drift in the short position.

Another study to analyze PEAD in Sweden is Hung et al. (2015) who examine how improvements in firm's financial reporting quality affect the drift. They measure such improvements by the switch from local financial reporting standards to international financial reporting standards (IFRS) and label the 2-year period before IFRS as the preshock period and the 2-year period post switching as the postshock period. In the Swedish market, they find 3-month daily BHAR of 5.54%, significant on the 5% level, for the preshock period and 1.91%, significant on the 10% level, for the postshock period (24.1% and 7.9% annually, respectively).

To the best of our knowledge, the only comprehensive study investigating PEAD in the Swedish market is Setterberg (2011) using a sample of stocks from the Stockholm Stock Exchange A-list in 1990-2005. Forming SUE-portfolios based on a time-series model, the author examines PEAD using buy-and-hold abnormal returns (BHAR) and calendar-time regressions on monthly returns data. For abnormal returns, the MSCI Sweden Index is used as a proxy for market returns. The study finds evidence of positive drift in the Swedish market when using BHAR with a magnitude of approximately 12% after a 12-month holding period. For the calendar-time portfolios, the monthly alpha after controlling for FF3 risk factors is 0.9% (11% annualized) for a PEAD trading strategy with a 12-month holding period and statistically significant on the 5% level. This result is primarily driven by the alpha of the long position, which is 0.7% and statistically significant at the 1% level, whereas the short position generates an alpha of -0.2%, not significant at conventional levels.

2.3 Explanations of the Anomaly

2.3.1 Risk and Limits to Arbitrage

Despite the extensive research on PEAD, there is no clear consensus on the underlying mechanisms driving the phenomenon (Fink, 2021). The empirical evidence suggest financial markets do not fully and immediately incorporate all publicly available information which directly challenges the semi-strong form of market efficiency, with Fama (1998) famously referring to PEAD as "the granddaddy of underreaction events".

Bernard and Thomas (1989) argue that the effect cannot be reconciled with mismeasurements of the Capital Asset Pricing Model (CAPM) or the Arbitrage-Pricing Theory (APT). Additionally, they investigate the argument that a zero-investment strategy such as PEAD generating positive mean returns due to its riskiness must periodically produce losses. Here, they find CARs to be consistently positive over time providing evidence that PEAD is not explained by risk. Instead, they point towards the drift stemming from delayed price responses and suggest two explanations: (i) a failure of market prices to fully recognize the serial correlation in quarterly earnings, and (ii) transaction costs.

Using time-series models, the serial correlation in quarterly earnings may be exploited to forecast future earnings, being strongest in adjacent quarters and having a seasonality component (e.g., Foster (1977); Griffin (1977)). Bernard and Thomas (1990) investigate this further and find a positive, but declining, relation in the three calendar quarters following earnings announcements, followed by a negative relation in the fourth quarter. The authors argue that this implies stock prices fail to incorporate the difference between firms' earnings series and a seasonal random walk.

While Bernard and Thomas (1989) suggest neither transaction costs nor short sale constraints can fully explain the drift, more recent studies are less definitive regarding the impact of trading frictions. Zhang et al. (2013) find that, using a four-factor asset pricing model, the PEAD strategy does not generate abnormal returns when transaction costs are controlled for, even in a quintile of the highest information risk. Conversely, Battalio and Mendenhall (2011) find positive drift returns when assuming large liquidity costs where they estimate a marginal investor to have been able to generate at least 14% yearly abnormal returns.

As found in Bernard and Thomas (1989) the PEAD anomaly is also linked to firm size where the drift tends to be larger in magnitude for smaller stocks. Related to this, Bhushan (1994) argues the link to size may stem from its inverse relation with transaction costs. Using share price and annual trading volumes as proxies for direct and indirect trading costs respectively, they find that including these variables subsumes the effect of size. However, Bartov et al. (2000) instead argue that the relationship between size and

PEAD may be driven by differences in investor sophistication, rather than by transaction costs.

Taking a step back from the specificity of transaction costs and considering limits to arbitrage in general, Martineau (2019) suggests stock prices' reactions to earnings announcements have become more efficient, especially for large US stocks. This is attributed to liquidity providers becoming more sophisticated. Similarly, Milian (2015) suggest that not only might there be unsophisticated investors, but also unsophisticated arbitrageurs, disrupting the arbitrage process. Furthermore, they find that for easy-to-arbitrage firms, the 10% most positive earnings announcement firms underperform the 10% most negative earnings announcement firms at their next earnings announcement.

Since the PEAD strategy involves short positions, investors face not only additional fees and risks such as short squeezes and counterparty risk, but also legal or mandate-based constraints on short-selling. In practice, a significant share of institutional investors, including many pension funds and mutual funds, are prohibited by regulation or investment policy from taking short positions (Shleifer and Vishny, 1997; Jones and Lamont, 2002; Barberis and Thaler, 2003). While market frictions may explain how the PEAD anomaly prevails over time, it fails to give substance to its origination.

2.3.2 The Behavioral Model

In behavioral finance, mispricings are caused by two major mechanisms: (i) limits to arbitrage making it difficult for rational traders to exploit mispricings, and (ii) behavioral biases that make the mispricings appear in the first place (Barberis and Thaler, 2003). The field of behavioral biases traces to the cognitive psychology research of Tversky and Kahneman (1974), who examines how individuals make decisions based on beliefs concerning the likelihood of uncertain events. They find that individuals rely on certain heuristics when faced with uncertainty regarding decisions, and that these heuristics lead to biases and systematic errors.

Relevant to PEAD, Griffin and Tversky (1992) suggest that individuals may overweight the strength of evidence while underweighting its statistical reliability, leading to underreaction when information is diagnostic but subtle. Barberis et al. (1998) extend these psychological findings to theoretical financial markets and propose that earnings announcements have low strength but high statistical weight. This assumption suggests stock prices will underreact to earnings announcements, generating the observed drift.

Alternatively, the theory by Daniel et al. (1998) suggests that PEAD could reflect a more complex behavioral pattern. If investors are overconfident in their private information and subject to self-attribution bias, they underreact to public information such as earnings news, and instead continue to trade based on their private beliefs. Hence, PEAD may reflect a continued overweighting of pre-event information post the earnings announcement. Empirical support from Liang (2003) reinforces this view, suggesting that overconfidence in private signals can contribute to the explanation of PEAD.

Together, these behavioral explanations suggest that PEAD is not merely a statistical anomaly or artifact, but a manifestation of deeper cognitive and psychological patterns in investor behavior. Hence, we proceed from the premise that correlated, systematic biases among investors contributes to the drift.

2.3.3 Information Uncertainty

As argued by Miller (1977), uncertainty leads to divergence in estimated valuations, and in the presence of short-selling constraints, this divergence of opinions results in prices being determined by the most optimistic subset of investors with the highest private valuations. Furthermore, Hirshleifer (2001) argues that greater uncertainty allows more space for behavioral biases. Combining Miller's theory with the overconfidence model of Daniel et al. (1998), Jiang et al. (2005) argues that earnings momentum strategies are predicted to be stronger for firms with higher information uncertainty.

Holthausen and Verrecchia (1988) presents a model for price changes in relation to the signals in sequential information releases. The model is built on the notion of two information releases where, in in the context of earnings announcements, the first can be viewed as the pre-earnings disclosure, i.e., what forms the markets expectations of the earnings, and the second as the actual earnings announcement. In this model, unexpected price changes after the second information release will be a function of the market's ex ante expectation as well as the market's belief about the noise in the information signal.

Building on this, our thesis focuses on the uncertainty related to the signal of unexpected earnings and how it influences PEAD through the medium of psychological biases. To clarify what we mean by uncertainty, we briefly review the definitions of risk and uncertainty. Based on the seminal work by Knight (1921) and descriptions by Keynes (1937), we separate risk and uncertainty as two distinct theoretical concepts. The definitions may be summarized in the following way (Anderson et al., 2009, p. 234):

> We adopt the position that an event is risky if its outcome is unknown but the distribution of its outcomes is known, and an event is uncertain if its outcome is unknown and the distribution of its outcomes is also unknown.

Imhoff and Lobo (1992) investigate the impact of firm-level uncertainty on stock price responses to earnings information. Using a CAPM-based measure of unexpected returns and scaling unexpected earnings and forecast dispersion by the stock price two trading days before the earnings announcement, they find that a greater ex ante forecast dispersion results in lower and less significant earnings response coefficients, and vice versa.

Taking the view that information uncertainty is correlated with investor overconfidence and arbitrage costs, Jiang et al. (2005) show that on average, firms with higher information uncertainty earn lower future returns and exhibit stronger price and earnings momentum effects. The authors measure earnings momentum by analyst forecast revisions and use 4 proxies for uncertainty: (i) firm age, (ii) return volatility, (iii) average daily turnover, and (iv) the duration of a firm's future cash flows.

Similarly, Zhang (2006) use 6 different proxies for information uncertainty including (i) market capitalization, (ii) firm age, (iii) analyst coverage, (iv) forecast dispersion, (v) stock volatility, and (vi) volatility of cash flow from operations. The study is motivated by the behavioral finance literature to test the joint hypothesis that if slow market responses to information is due to behavioral biases, these biases will be larger, and thus the price response slower, when there is more ambiguity about the implications of the information regarding a firm's value. Using analyst forecast revisions as proxy for positive and negative earnings news, the author finds that greater information uncertainty leads to higher abnormal returns following good news and vice versa.

Conversely, Francis et al. (2007) take the view that PEAD may rather be explained through rational learning by a model of structural uncertainty where Bayesian investors face uncertainty about shifts in the payoff structure of investments. The authors use the difference between reported and forecasted earnings scaled by price as proxy for earnings surprise, and the Dechow and Dichev (2002) measure of earnings quality, capturing the mapping of the current accruals portion of earnings into cash flows, as proxy for information uncertainty. They find that the initial market reaction is attenuated for high-uncertainty firms and that PEAD portfolios formed on high-uncertainty firms generate higher abnormal returns. Thus, while taking a rational perspective rather than behavioral, and measuring uncertainty using accounting metrics, Francis et al. (2007), in line with Zhang (2006) and Jiang et al. (2005), find that the price continuation is greater for firms with higher information uncertainty.

Gerard (2012) explore the link between information uncertainty and PEAD in Europe, and find that the trading strategy generates higher abnormal returns when only including the subset of stocks with higher information uncertainty, proxied by idiosyncratic volatility. Furthermore, the author finds that the abnormal return of the PEAD trading strategy is primarily generated during periods when the aggregate idiosyncratic risk in the market is elevated, suggesting a time-varying and state-dependent component to the magnitude of the drift.

2.3.4 Investor Sentiment

Baker and Wurgler (2006) propose two channels through which investor sentiment affects the cross-section of stock returns, considering a mispricing that arises from a combination of uninformed demand shocks and limits to arbitrage. First, they suggest that investor sentiment could be viewed as a proxy for investors' propensity to speculate. This suggests that sentiment correlates with the relative demand for speculative assets, causing overpricing during high sentiment and underpricing during low sentiment, even if arbitrage forces are constant across stocks. Second, they suggest that investor sentiment may be viewed as optimism or pessimism about stocks in general, but that the ability to arbitrage varies between stocks. This would allow mispricings such as PEAD to persist longer in stocks that are hard to arbitrage. These channels are likely to have overlapping effects, but also to reinforce each other.

To quantify the level of investor sentiment in the market, Baker and Wurgler (2006) develop an index based on a composite of 6 market indicators to reflect different dimensions of sentiment-driven investor behavior such as optimism, risk appetite, and speculative enthusiasm: (i) the closed-end fund discount, (ii) trading volume[1], (iii) the number of IPOs, (iv) the average first-day returns of IPOs, (v) the equity share in new issues, and (vi) the dividend premium. Using this index, the authors find that when sentiment is high, stocks that are attractive to speculative investors, but unattractive to arbitrageurs[2], tend to generate relatively low subsequent returns. When sentiment is low, this pattern tends to attenuate or even reverse. Furthermore, they observe that the immediate market reaction to earnings announcements is generally weaker during periods of high sentiment.

Examining US stocks over 1972-2007 and using CARs, Mian and Sankaraguruswamy (2012) find that stock price reactions to earnings news are influenced by the prevailing investor sentiment, measured by the Baker-Wurgler index. Specifically, during periods of high sentiment, the market reacts more strongly to positive earnings surprises in the short window around the announcement, while in periods of low sentiment the reaction is more pronounced for negative surprises. Moreover, they show that this pattern persists in the 3-months following earnings announcements, with portfolios sorted on unexpected earnings exhibiting higher abnormal returns during high sentiment periods compared to low sentiment periods.

Livnat and Petrovits (2019) find evidence challenging that of Mian and Sankaraguruswamy (2012). Also using the Baker-Wurgler index and a US sample from an overlapping period of 1987-2005, their study indicates that the positive drift following positive earnings surprises is stronger in low sentiment periods than in high and vice versa. Specifically, they find that extreme good news stocks following periods of low sentiment generate significantly higher excess returns than those following periods of high sentiment.

While these findings are contradictory, they indicate a relationship between investor sentiment and PEAD. We also note that the literature on sentiment and PEAD has primarily examined the returns of the underlying portfolios, rather than the PEAD hedge strategy itself.

Expanding beyond PEAD, Stambaugh et al. (2012) examines how investor sentiment, proxied by the Baker-Wurgler index, influences the profitability of long-short trading strategies that exploits various market anomalies. They find that profitability is higher during periods of high sentiment, driven primarily by returns in the short leg rather than the long leg.

[1]Measured by NYSE turnover. However, due to the rise of institutional high-frequency trading and the fragmentation of trading across multiple venues, trading volume is no longer included in the index construction.

[2]Such as younger, smaller, high-growth, and unprofitable firms.

2.3.5 Joint Effects of Uncertainty and Sentiment

To the best of our knowledge, Bird and Yeung (2012) is the first study to examine the joint effects of uncertainty and sentiment on PEAD. The authors use Australian data from 2001-2007 and measure unexpected earnings as the difference between announced earnings and last year's earnings standardized by total assets. They proxy market-level uncertainty by (VIX) and sentiment through two alternative proxies: (i) return momentum of the ASX200 index and (ii) an Australian monthly consumer sentiment measure. They find that in periods of high uncertainty and low sentiment, the market reacts more strongly to negative earnings announcements and vice versa.

In Bird et al. (2014), the authors instead use US data from 1986-2009. Unexpected earnings are measured as the difference between actual and expected EPS, scaled by the actual EPS. Market-level uncertainty is measured using VIX and sentiment is proxied by realized S&P 500 index returns. Their reasoning is that they want to capture short-term variations in sentiment where the monthly frequency of the Baker-Wurgler index is lacking granularity. They conclude that the level of market uncertainty and the prevailing investor sentiment in the post announcement period influences PEAD.

Goh and Yang (2025) investigate stock-level valuation uncertainty combined with investor sentiment proxied by the Baker-Wurgler index. Their study finds that uncertainty and sentiment influences PEAD, where the drift is most pronounced when earnings surprises conflict with sentiment, especially for stocks with higher uncertainty.

2.4 Hypothesis Development

As presented in Section 2.3, PEAD may arise from a combination of the behavioral biases of investors and limits to arbitrage. Consistent with PEAD's documented global prevalence, these factors are not unique to any single market. By extension, this supports the possibility of PEAD being present in the Swedish market, further reinforced by previous evidence of PEAD in Sweden (Griffin et al., 2010; Setterberg, 2011; Hung et al., 2015). Based on this, we formulate our first hypothesis:

Hypothesis 1: PEAD is present in the Swedish equity market during the period 2005Q1 to 2023Q1.

Considering the theoretical foundations of Tversky and Kahneman (1974) presented in Section 2.3.3 and defining uncertainty as a separate concept from risk, we propose that uncertainty will have an effect on the formation of stock prices. Considering the results of the previous related literature (Imhoff and Lobo, 1992; Jiang et al., 2005; Zhang, 2006; Francis et al., 2007), we formulate our second hypothesis:

Hypothesis 2: Stocks with higher information uncertainty exhibit greater PEAD than *stocks with lower information uncertainty.*

If sentiment serves as a proxy for the speculative behavior of sentiment-driven investors, as argued by Baker and Wurgler (2006) and presented in Section 2.3.4, and if PEAD arises due to investor biases, as suggested by the behavioral finance explanation presented in Section 2.3.2, a relationship between PEAD and sentiment is expected. Given the mixed empirical evidence and the limited research on the link between investor sentiment and the profitability of the PEAD trading strategy, we propose our third hypothesis:

Hypothesis 3: Investor sentiment has an effect on the abnormal return of the PEAD strategy.

As discussed in Sections 2.3.3 and 2.3.4, information uncertainty and investor sentiment have been shown to individually influence PEAD. Furthermore, as presented in Section 2.3.5, a limited body of research on the subject has found evidence for additional explanatory power in cross-section of the two variables. Based on this coupled effect, we formulate our fourth hypothesis:

Hypothesis 4: Incorporating information uncertainty and investor sentiment will increase the abnormal returns of the PEAD strategy.

3. Empirical Methodology

3.1 Data Collection and Sample Construction

We use two analytical frameworks to test our hypotheses. First, we examine PEAD in event-time using the exploratory methodology of Bernard and Thomas (1989) and Cumulative Abnormal Returns (CAR) to investigate the magnitude, timing, and graphical representation of the drift. Second, we examine PEAD in calendar-time following the methodology of Chan et al. (1996) to evaluate the anomaly, and the potential for a trading strategy that exploits it to generate abnormal returns, from the practical perspective of an investor.

We construct our sample dataset based on earnings announcement events for firms listed on the Stockholm Stock Exchange (SSE) over 2005Q1-2023Q1.[3] We retrieve quarterly earnings announcements and analyst earnings forecasts from the Institutional Brokers Estimate System (IBES) detail database through Wharton Research Data Services (IBES, 2025), stock market data from FinBas at Swedish House of Finance Research Data Center (FinBas, 2025), investor sentiment data from Jeffrey Wurgler's website (Wurgler,

[3]Data from 2004Q4 is used to create earnings surprise cutoffs for the first quarter in our sample, see Section 3.2 for more details.

2025), currency exchange rates and the Swedish short-term rate from Sveriges Riksbank's website (Sveriges Riksbank, 2025), and the Morgan Stanley Capital International (MSCI) Sweden Index with net reinvested dividends from the index website (MSCI Inc., 2025).

From the FinBas database, we use adjusted daily closing prices, total market values, and book values. As IBES and FinBas does not share a common key, we follow the methodology of Anderson et al. (2020) and merge the datasets manually based on ticker and company name. Additionally, since Swedish equities may have several share classes listed, we select only one to represent each company where we aspire to keep the most liquid and representative share class as determined by trading volume and market capitalization. Furthermore, we manually remove erroneous FinBas data[4] and stocks on the unofficial quotations list. When EPS, stock price, market value, or book value is not reported in Swedish Krona (SEK), we convert the observations to SEK using Sveriges Riksbank's daily exchange rates. We exclude stocks with a book-to-market below 0. As FinBas reports market values monthly, we forward-fill these values for the subsequent month. When FinBas does not report a price for up to two consecutive days, we use linear interpolation to fill these gaps to avoid removing illiquid stocks.

3.2 Earnings Surprises, Uncertainty, and Portfolio Formation

Conceptually, PEAD analysis compares the relative performance of portfolios sorted by the magnitude of earnings surprises. As presented in Section 2.2.2, the PEAD literature typically employs one of three approaches to approximate the surprise: (i) time-series regressions, (ii) earnings announcement returns, or (iii) analyst consensus forecasts. We use analyst forecasts for two reasons. First, they provide a forward-looking, market-based proxy in which analysts' predictions serve as a reasonable substitute for the market's expectations. Second, because Livnat and Mendenhall (2006) find that the drift is larger with analysts' forecasts compared with time-series models.

Following the seminal contributions in the field (Foster et al., 1984; Bernard and Thomas, 1989), we adopt Standardized Unexpected Earnings (SUE) as our measure of earnings surprises. SUE is defined as unexpected earnings (UE), i.e., the actual earnings less the markets' ex ante expectations, standardized to increase comparability between firms. Consistent with the literature that uses analyst forecasts as a proxy for market expectations, we compute UE for each earnings announcement event as the difference between the actual reported EPS (ACT_i) and the median analyst forecast (EST_i). In the spirit of "Model 1" in Foster et al. (1984), we scale by the absolute value of the actual reported EPS and construct or measure as defined in Equation 1.

$$SUE_i = \frac{ACT_i - EST_i}{|ACT_i|} \tag{1}$$

[4] Such as CDON Group AB where the reported share price jumps back and forth between CDON and Nelly Group, likely due to the spin-off of CDON from Qliro (renamed to Nelly) in 2020.

We retrieve data to construct SUE from the IBES detail database. Following the methodology of Livnat and Mendenhall (2006), we use individual analyst forecasts of the Earnings per Share (EPS) made within 90 days prior to the earnings announcement. If an analyst provides multiple forecasts within this time window, we consider only the most recent forecast. Furthermore, we only include forecasts using the EPS type (primary or diluted) most commonly used by analysts for each earnings announcement. We aggregate the individual forecasts to extract the median estimate (EST_i), dispersion of analyst estimates ($DISP_i$), and analyst coverage (COV_i) for each event. We also extract the actual reported EPS (ACT_i) and the date of the earnings announcement.

To mitigate the effect of potentially erroneous data, we truncate the top and bottom 2.5% of the SUE distribution. Within each quarter, we assign each earnings announcement event to an earnings surprise quintile group based on SUE. To avoid hindsight bias, the cutoff values for each group are determined using the distribution of SUE from the preceding quarter.[5]

As presented in Section 2.3.3, there are several metrics to proxy firm-level information uncertainty. Following Zhang (2006) we use the inverse of market capitalization ($\frac{1}{MV}$) as our proxy for information uncertainty in the main analysis and assign each earnings announcement to an uncertainty group within each quarterly SUE grouping.[6] Due to the limited size of our sample, each SUE group is divided into two different uncertainty groups, "Low" and "High", rather than tertiles such as in Jiang et al. (2005) or deciles such as in Francis et al. (2007); Zhang (2006). Hence, we construct five portfolios based on earnings surprise, each further split into two uncertainty groups, resulting in ten portfolios in the cross-section of the two variables.

3.3 Sentiment Classification

Following Livnat and Petrovits (2019), we classify each sample month into investor sentiment tertiles based on the Baker-Wurgler index. To avoid hindsight bias, each month is classified based on the historical distribution up to that point. Sentiment is classified as low if the value falls within the bottom 30% of preceding values, as high if it falls within the top 30%, and otherwise as neutral.

In Figure 1, we observe the co-movement of the sentiment index and the MSCI Sweden Index. We argue this justifies the use of a sentiment index based on U.S. market metrics as a reasonable proxy for investor sentiment in Sweden, built on the notion of global interconnectedness in financial markets.

[5]For example, SUE groups in 2005Q1 are assigned based on the distribution of SUE in 2004Q4.

[6]For example, events in 2005Q1 and within SUE group 5 are further divided into uncertainty groups.

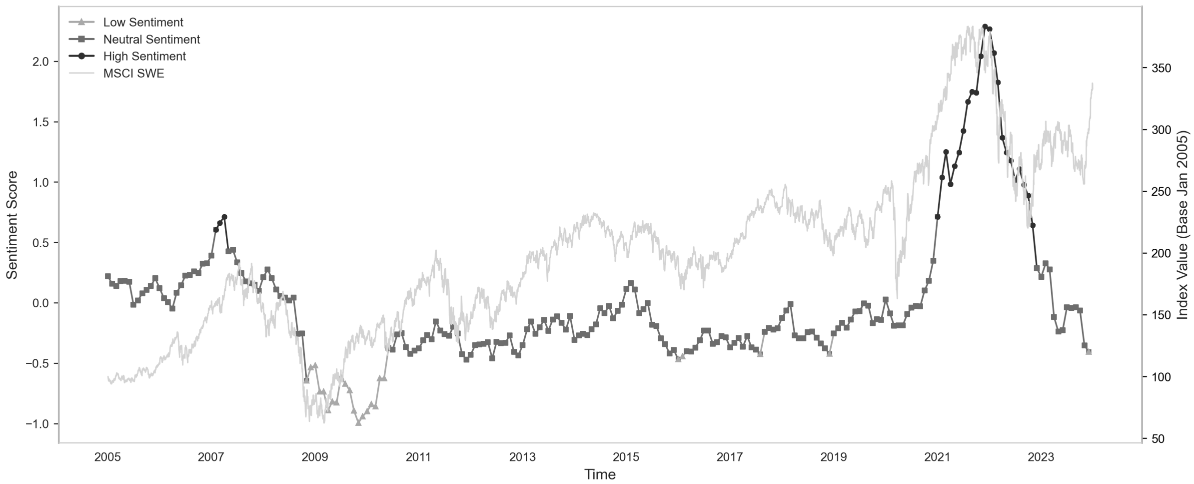

Figure 1: Baker-Wurgler sentiment index over time, categorized into low, neutral, and high sentiment based on the relative historical 30th and 70th percentile thresholds. Sentiment classifications are indicated by markers. The figure also shows the MSCI Sweden Index (Net), rebased to 100 in January 2005, on a secondary axis to provide a visual reference for Swedish equity market developments during the corresponding sentiment phases.

3.4 Event-Time: Cumulative Abnormal Returns

We conduct an event study based on Cumulative Abnormal Returns (CARs). We use CARs rather than Buy-And-Hold Abnormal returns (BHAR) since they pose fewer statistical problems for short-term event studies according to Fama (1998). We define daily abnormal returns as the difference between actual returns and expected returns as shown in Equation 2. Following Livnat and Mendenhall (2006), we use a factor-adjusted model ($E[R_{i,t}] = R_{p,t}$) where expected returns are proxied by the daily returns of a portfolio with approximately the same size and book-to-market ratio. We construct these portfolio returns following the methodology of Sodini et al. (2022).[7]

$$AR_{i,t} = R_{i,t} - E[R_{i,t}] \tag{2}$$

For each event, we calculate the Cumulative Abnormal Returns (CARs) over multiple time periods, as defined in Equation 3. We define the full event window to begin one trading day prior to the earnings announcement and extend up to 60 trading days afterward. To ensure consistency in measurement, we include only events with a complete return series over the full event window. We calculate CAR for the immediate announcement window ($t \in [-1, 1]$), the first post-announcement month ($t \in [2, 20]$), the second month ($t \in [21, 40]$), the third month ($t \in [41, 60]$), as well as the full 3-month period following the announcement ($t \in [2, 60]$).[8] This allows us to assess the immediate market reaction, when the drift occurs, as well as the persistence of abnormal returns across a quarterly horizon while lowering the influence of overlapping or confounding events such

[7]See Appendix A for more details.

[8]We approximate one calendar month by 20 trading days.

as subsequent earnings announcements.

$$CAR_i(t_0, t_1) = \sum_{t=t_0}^{t_1} AR_{i,t} \tag{3}$$

To examine the CARs for the portfolios described in Section 3.2, we calculate the average Cumulative Abnormal Return. To assess whether the CAR for a given portfolio and event window is statistically different from zero ($E[CAR_p] = 0$), we use a one-sample t-test. We denote the PEAD trading strategy, i.e., the portfolio that takes a long position in the highest earnings surprise quintile and a short position in lowest earnings surprise quintile, as:

$$PEAD = CAR_{SUE5} - CAR_{SUE1} \tag{4}$$

To formally test the PEAD strategy, we restate our first hypothesis from Section 2.4 in statistical terms and assess its significance using an independent two-sample Welch's t-test:

Hypothesis 1: $PEAD \neq 0$.

To test our second hypothesis from Section 2.4, we construct the PEAD strategy separately for high uncertainty (HU) and low uncertainty (LU) portfolios, and formalize the hypothesis as:

Hypothesis 2: $PEAD_{HU} > PEAD_{LU}$.

We assess the significance of this difference using a Wald test for two independent estimates, with p-values computed under the standard normal distribution.

Considering the sensitivity of the CAR methodology to idiosyncratic shocks in small samples, combined with the limited number of events in the low and high investor sentiment regimes, hypotheses 3 and 4 are not examined using the event-time approach. For further details about the CAR methodology including test statistics, see Appendix B.

3.5 Calendar-Time: Jensen's Alpha Approach

Following the work of Chan et al. (1996), we further examine PEAD using calendar-time portfolio regressions (CTR). In this approach, we regress the monthly return of a portfolio on a set of risk factors, such as the Capital Asset Pricing Model (CAPM) by Sharpe (1964); Lintner (1965), the Fama-French 3-factor model (FF3) by Fama and French (1993) or the Fama-French-Carhart 4-factor model (FFC4) by Carhart (1997). Any return not explained by the model of risk factors (i.e., the α) is considered abnormal

(Jensen, 1968). This methodology offers a perspective on the risk-adjusted performance of a trading strategy from an investor's point of view.

Similar to other studies using the calendar-time methodology, we shift from a daily to a monthly perspective by aggregating our daily return series into a monthly return series. To mitigate the potential of selection bias arising from ignoring negative returns from involuntary delistings, we assign a return of -30% to the final observation in each firm's monthly return series.[9] Furthermore, to avoid hindsight bias, each firm-quarter event is assigned to a portfolio formation date corresponding to the first day of the quarter following the earnings announcement.[10] While this approach may exclude the portion of the drift that occurs between the earnings announcement and the portfolio formation date, it ensures that the strategy is implementable in a real-time setting. For companies that report earnings for two different fiscal quarters within the same calendar quarter, only the announcement closest to the portfolio formation date is retained.

Our sample includes 73 portfolio formation dates, ranging from April 2005 to April 2023. Sentiment categories are assigned to each portfolio based on the sentiment level in the month of portfolio formation. In our sample, 7 formation dates are classified as low sentiment, 57 neutral sentiment, and 9 high sentiment. For each formation date, we compute the equally-weighted average monthly excess return, as shown in Equation 5, for each of the portfolios introduced in Section 3.2, and for each month of the holding period. We calculate excess returns as the portfolio return less the return of a risk-free asset ($R_{rf,m}$), proxied by the Swedish 1-month treasury bill. We use a 3-month holding period, resulting in a total of 219 monthly portfolio returns used in the regressions. Of these, 21 correspond to portfolios formed during low sentiment periods, 171 during neutral sentiment, and 27 during high sentiment.

$$R_{p,m} = \left(\frac{1}{N_p} \sum_{i \in p} R_{i,m} \right) - R_{rf,m} \tag{5}$$

To evaluate the PEAD strategy, we construct a hedge portfolio by computing the difference in returns between the highest and lowest SUE groups (SUE5 and SUE1, respectively), as shown in Equation 6:

$$R_{PEAD,m} = R_{SUE5,m} - R_{SUE1,m} \tag{6}$$

To evaluate the risk-adjusted performance of the portfolios, we use three asset pricing models. First, we apply the CAPM by regressing the excess returns of each portfolio, including the PEAD portfolio, on the excess market return ($RMRF$), proxied by the return of the MSCI Sweden Index with net reinvested dividends in excess of the Swedish

[9] An assumption based on the approximations of Shumway (1997) and tested in the robustness checks in Section 4.3.

[10] For example, if the announcement occurs in January, February, or March, the event is assigned to the portfolio formed on April 1st.

1-month treasury bill. This model is shown in Equation 7.

$$R_{p,m} = \alpha + \beta RMRF_m + \epsilon \tag{7}$$

Second, we apply the FF3 model, which augments the CAPM by including the size (SMB) and value (HML) risk factors.[11] This model is shown in Equation 8.

$$R_{p,m} = \alpha + \beta RMRF_m + sSMB_m + hHML_m + \epsilon \tag{8}$$

Third, we use the FFC4 model, which builds on the FF3 model and also includes the momentum risk factor (UMD).[12] This model is shown in Equation 9.

$$R_{p,m} = \alpha + \beta RMRF_m + sSMB_m + hHML_m + mUMD_m + \epsilon \tag{9}$$

We estimate these models using Ordinary Least Squares (OLS) regressions with Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors. In each regression, a positive and statistically significant constant term (α) indicates that an investor could earn a gross risk-adjusted abnormal monthly return. Accordingly, our first hypothesis, namely to identify the PEAD, is tested directly within the regression and formalized as follows:

Hypothesis 1: $\alpha_{PEAD} \neq 0$

To test our second hypothesis, we compare the risk-adjusted abnormal returns of a PEAD strategy that invests exclusively in high-uncertainty (HU) stocks with that of a strategy focused solely on low-uncertainty (LU) stocks. We therefore formalize Hypothesis 2 as follows:

Hypothesis 2: $\alpha_{HU} > \alpha_{LU}$

Given the overlap in sample periods and the likelihood of correlated error terms between the two strategies, we utilize the Seemingly Unrelated Regressions (SUR) framework to jointly estimate the models and obtain the corresponding variance-covariance matrix (Zellner, 1962). We then test our hypothesis using a Wald test (Mize et al., 2019). This methodology is effectively the same as Francis et al. (2007) use to compare high- and low-uncertainty portfolios, and render the same estimates, while allowing for the testing of a directional hypothesis. For further details about the CTR methodology including test statistics, see Appendix C.

For our third hypothesis, we examine whether the performance of the PEAD strategy varies with the prevailing investor sentiment. We introduce two dummy variables into

[11] See Appendix A for construction of the SMB and HML risk factors.

[12] See Appendix A for construction of the UMD risk factor.

Equation 9: D_{HS}, which equals 1 during periods of high sentiment (HS), and D_{LS}, which equals 1 during periods of low sentiment (LS). The resulting model is specified in Equation 10.

$$R_m = \alpha + \delta_{HS} D_{HS} + \delta_{LS} D_{LS} + \beta RMRF_m + sSMB_m + hHML_m + mUMD_m + \epsilon \quad (10)$$

If investor sentiment has a statistically significant effect on risk-adjusted abnormal returns post earnings announcements, we expect δ_{HS} and/or δ_{LS} to be significantly different from zero. We test these effects both individually and jointly, formalizing our third hypothesis in two parts:

Hypothesis 3.1: $\delta_{HS} \neq 0$

Hypothesis 3.2: $\delta_{LS} \neq 0$

Our fourth hypothesis compares the abnormal returns of the standard PEAD strategy with those of a selective PEAD strategy incorporating sentiment and uncertainty. This hypothesis is tested using the same SUR estimation and Wald test methodology as in Hypothesis 2 and we formalize it as follows:

Hypothesis 4: $\alpha_{Selective} > \alpha_{PEAD}$

3.6 Descriptive Statistics

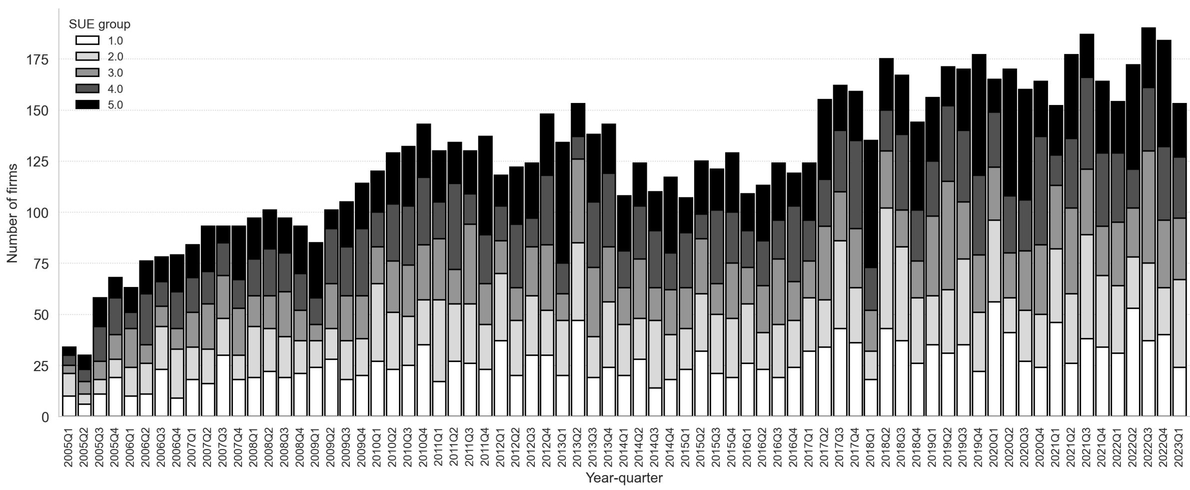

Figure 2: Quarterly distribution of the number of firms across standardized unexpected earnings (SUE) quintiles from 2005Q1 to 2023Q1.

Our sample consists of 9,270 earnings announcement events with the distribution over time shown in Figure 2. The number of observations per quarter increases over time, where 2005Q2 has the lowest number of observations at 30 firms whereas 2022Q3 has the highest number of observations at 190 firms. The distribution across earnings surprise groups varies by quarter, as the cutoffs are determined by the SUE distribution of the preceding quarter.

From Table 1 Panel A, we observe that the daily stock returns ($R_{i,t}$) in our sample data range between -84.49% to 172.53%. While these values may appear extreme for daily stock returns, closer examination confirms their validity.[13] Comparing daily stock returns with daily market returns ($R_{Mkt,t}$), we note that the means are 0.05% and 0.04%, respectively, indicating similar average performance, while the medians differ at 0.00% and 0.06%. This is consistent with the stylized fact that individual stock returns tend to be positively skewed, whereas aggregate market returns often exhibit negative skewness.

The standard deviation of the daily stock returns of 2.50% is higher than the standard deviation of the daily market returns of 1.78%. This higher volatility is likely due to the MSCI index construction which excludes smaller stocks that tend to be more volatile but also because technically a portfolio of stocks tends to have lower volatility in line with diversification according to Modern Portfolio Theory (Markowitz, 1952). We note that the extreme values of the monthly stock returns ($R_{i,m}$), -85.13% and 185.74%, are close those of the daily stock returns. This suggests that the most extreme returns found in our sample are single occurrences and not necessarily continuing for an entire month.

We observe that the mean of actual reported EPS (ACT) is slightly lower than the mean of median analyst forecasted EPS (EST), 2.11 compared to 2.30. This suggests the presence of a positive bias among forecasters, consistent with the findings of Lim (2001). The median number of analysts providing a forecast for each earnings announcement (COV) is 2, implying that at least half of the sample consists of estimates constructed using at least two estimates. To be more precise, 5,871 observations have at least two analysts, which is why this is the number of observations where the dispersion of analyst forecasts scaled by the stock price at the end of the month preceding the announcement ($DISP$) is defined. Furthermore, we note that the maximum $DISP$ value of 2,350% is extreme. However, only 11 observations exceed 100%[14], suggesting that such outliers are rare and unlikely to materially change the results.

The volatility of weekly excess returns over the 52 weeks leading up to the earnings announcement ($SIGMA$) ranges from 1.53% to 38.35%. It is only available for 9,216 observations, reflecting the fact that a full 52-week history is required prior to the announcement for the measure to be included in our analysis. While this may introduce selection bias by excluding younger firms, this only constitutes 54 firm-quarter observations and the measure is used solely in the robustness checks.

[13] Both extreme values are pharmaceutical companies disclosing results of phase III-studies.

[14] Of these 11 observations, 10 are related to earnings announcements for Lundin Petroleum.

Table 1: Descriptive Statistics of Sample Data

Panel A: Summary Statistics

Variable	N	Mean	Std	Min	25th	Median	75th	Max
$R_{i,t}$	546,631	0.05%	2.50%	-84.49%	-1.08%	0.00%	1.11%	172.53%
$R_{Mkt,t}$	4,632	0.04%	1.78%	-13.77%	-0.79%	0.06%	0.94%	15.09%
$R_{i,m}$	27,625	1.03%	11.19%	-85.13%	-4.82%	0.67%	6.49%	185.74%
ACT	9,270	2.11	27.75	-340.02	0.35	0.96	1.90	975.11
EST	9,270	2.30	22.45	-154.91	0.38	0.96	1.85	814.30
COV	9,270	3.32	2.99	1	1	2	4	26
$DISP$	5,871	1.69%	35.86%	0.00%	0.09%	0.19%	0.44%	2,350%
$SIGMA$	9,216	4.79%	2.10%	1.53%	3.41%	4.33%	5.62%	38.35%
MV	9,270	34,662	72,407	33	2,262	7,337	27,363	726,768
BV	9,270	14,047	31,793	4	807	2,482	11,274	319,111

Panel B: Pearson Correlation Matrix

	ACT	EST	SUE	COV	$DISP$	$SIGMA$	MV	BV
ACT	1.00							
EST	0.91	1.00						
SUE	0.06	0.00	1.00					
COV	0.03	0.03	0.10	1.00				
$DISP$	0.00	0.00	-0.01	0.02	1.00			
$SIGMA$	-0.00	0.01	-0.09	-0.18	0.03	1.00		
MV	0.00	-0.00	0.09	0.62	-0.01	-0.20	1.00	
BV	0.00	-0.00	0.07	0.58	-0.01	-0.17	0.79	1.00

Panel A shows summary statistics of key variables while Panel B reports their respective pairwise Pearson correlation coefficients excluding the return variables. $R_{i,t}$ is the daily stock return for all firm-days included in the sample used for event time analysis spanning from day $t = -1$ to day $t = +60$. $R_{Mkt,t}$ is the daily market return proxied by MSCI Sweden Index Net for all trading days included in the sample. $R_{i,month}$ is the monthly stock return used for calendar time analysis spanning from the formation date of the portfolio and the next three months. Actual earnings per share (ACT) and median analyst forecasted EPS (EST) are recorded for each firm-quarter. Analyst coverage (COV) is measured as the number of unique analyst providing an estimate and dispersion of analyst forecast ($DISP$) is measured as the standard deviation of forecasts scaled by the stock price at the end of the month preceding the announcement. Stock return volatility ($SIGMA$) is the volatility of weekly excess returns in the 52 weeks prior to that of the earnings announcement. Firm size (MV) is measured as market capitalization in MSEK at the end of the month closest to the earnings announcement. Book value (BV) is reported in MSEK as of the most recent December prior to the announcement.

The mean market value of equity (MV) is 34,662 MSEK whereas the median is lower at 7,337 MSEK. This suggests our sample is skewed toward smaller companies, consistent with their greater prevalence in the market. Furthermore, we note that the minimum book value of equity (BV) is positive at 4, reflecting our methodological decision to include only firms with a positive book-to-market ratio.

From the correlation matrix, Table 1 Panel B, we observe ACT and EST are positively correlated at 0.91, indicating that forecasters are, to some extent, able to predict earnings. We note that SUE is not correlated with EST and has a very low correlation of 0.06 with ACT. This is expected, as SUE is designed to capture the unexpected component in the difference between actual and forecasted earnings.

We find a relatively high positive correlation of 0.62 between COV and MV. This is expected since firms covered by more analysts tend to be larger (Livnat and Mendenhall, 2006). Furthermore, $SIGMA$ shows negative correlation with COV, MV, and BV, indicating the stylized fact of smaller stocks to be more volatile than larger stocks.

In Table 2, we observe that the full sample is reasonably well-distributed across portfolios formed on earnings surprise (SUE) and information uncertainty. Within each earnings surprise portfolio, the low-uncertainty group is slightly smaller than the high-uncertainty group. This is a result from the cutoff method used: when an earnings surprise portfolio contains an odd number of observations, the high-uncertainty group is allocated one additional observation.

For our earnings surprise variable (SUE), we find that it increases monotonically with the SUE-group, confirming that the portfolio allocation functions as intended. Additionally, the quarterly portfolios have similar minimum and maximum sizes, typically ranging from 2-3 to 26-31 firms, with median sizes between 11 and 13. Based on the distribution shown in Figure 2, we conclude that smaller quarterly portfolios are concentrated at the beginning of the sample period, while larger portfolios appear towards the end. We further note that the high-uncertainty portfolios consist of firms with smaller market capitalization, consistent with our chosen proxy for uncertainty.

Table 2: Descriptive Statistics per SUE and Uncertainty Portfolio

Portfolio			SUE	Firms per Quarter			MV		
SUE	Uncertainty	N	Mean	Min	Median	Max	Min	Median	Max
High (5)	High	982	0.40	2	13	31	39	1,872	37,598
High (5)	Low	947	0.34	2	12	31	1,650	17,847	502,371
4	High	918	0.11	3	12	27	111	4,099	36,298
4	Low	881	0.11	2	12	26	1,160	45,459	491,994
3	High	878	0.01	2	11	28	33	4,866	55,450
3	Low	847	0.01	2	11	27	4,271	50,378	726,768
2	High	968	-0.13	3	13	30	89	2,855	27,780
2	Low	931	-0.11	2	12	29	2,585	30,848	615,930
Low (1)	High	976	-0.97	3	12	28	39	1,018	18,118
Low (1)	Low	942	-0.89	3	12	28	612	10,164	349,314
Full sample		9270	-0.12	30	129	190	33	7,337	726,768

Descriptive statistics for the ten portfolios formed by SUE quintiles and uncertainty classification as well as for the full sample. The table presents the total number of observations (N), the average standardized unexpected earnings (SUE), and the minimum, mean, and maximum number of firms per quarter, along with corresponding values for market capitalization (MV).

4. Results, Robustness Tests, and Implications

4.1 Event-Time Analysis

Table 3: Cumulative Abnormal Returns (CARs) by SUE Quintiles

SUE group	N	CAR(-1,1)	CAR(2,20)	CAR(21,40)	CAR(41,60)	CAR(2,60)
High (5)	1929	3.25%***	0.20%	0.33%*	0.08%	0.61%*
		(0.0018)	(0.0019)	(0.002)	(0.0022)	(0.0034)
4	1799	2.34%***	0.08%	0.03%	0.23%	0.35%
		(0.0014)	(0.0017)	(0.0018)	(0.0019)	(0.003)
3	1725	0.71%***	-0.45%***	0.25%	-0.07%	-0.26%
		(0.0014)	(0.0016)	(0.0017)	(0.0019)	(0.003)
2	1899	-1.04%***	-0.51%***	0.24%	-0.17%	-0.44%
		(0.0015)	(0.0018)	(0.0018)	(0.0021)	(0.0031)
Low (1)	1918	-2.86%***	-1.12%***	-0.42%*	-0.68%**	-2.22%***
		(0.0017)	(0.0023)	(0.0023)	(0.0027)	(0.0042)
PEAD		6.11%***	1.32%***	0.75%**	0.76%**	2.83%***
		(0.0025)	(0.003)	(0.003)	(0.0035)	(0.0054)

Average cumulative abnormal returns (CARs) for portfolios sorted by standardized unexpected earnings (SUE) quintiles across event windows, where day 0 is the earnings announcement date. Abnormal returns are calculated as the difference between the daily stock return and the return of a value-weighted benchmark portfolio matched on firm size and book-to-market ratio. Columns report CARs for the immediate window CAR(-1,1), the first month CAR(2,20), the second month CAR(21,40), the third month CAR(41,60), and the full quarter CAR(2,60). The "PEAD" row shows returns to a long-short strategy that takes a long position in the highest SUE quintile and a short position in the lowest. Standard errors are shown in parentheses. Two-sided p-values are reported. Significance levels are indicated by: ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

In Table 3, CAR(-1,1) reflects the immediate market response to earnings news. Consistent with the semi-strong form EMH, it is statistically significant at the 1% level across all earnings surprise groups and increases monotonically with the magnitude of the earnings surprise, from -2.86% to 3.25%. These results confirm that the market, to some extent, rapidly incorporates earnings information into prices, and that the information content to be incorporated is associated with our earnings surprise measure.

Examining the full quarter (CAR(2,60)), we find that the CAR of the highest earnings surprise portfolio is 0.61% and significant on the 10% level whereas the lowest earnings surprise portfolio is -2.22% and statistically significant on the 1% level. The resulting CAR of the PEAD strategy is 2.83% and statistically significant on the 1% level. These results support the existence of PEAD in our sample and thus our first hypothesis. In the first month (CAR(2,20)), second month (CAR(21,40)), and third month (CAR(41,60)), after the announcement, we find that PEAD accumulates gradually. The positive drift for the highest SUE group appears concentrated in the second month after the announcement, whereas for the low SUE group the drift accumulates steadily over time, with the first month contributing the most. This pattern is also seen in Figure 3.

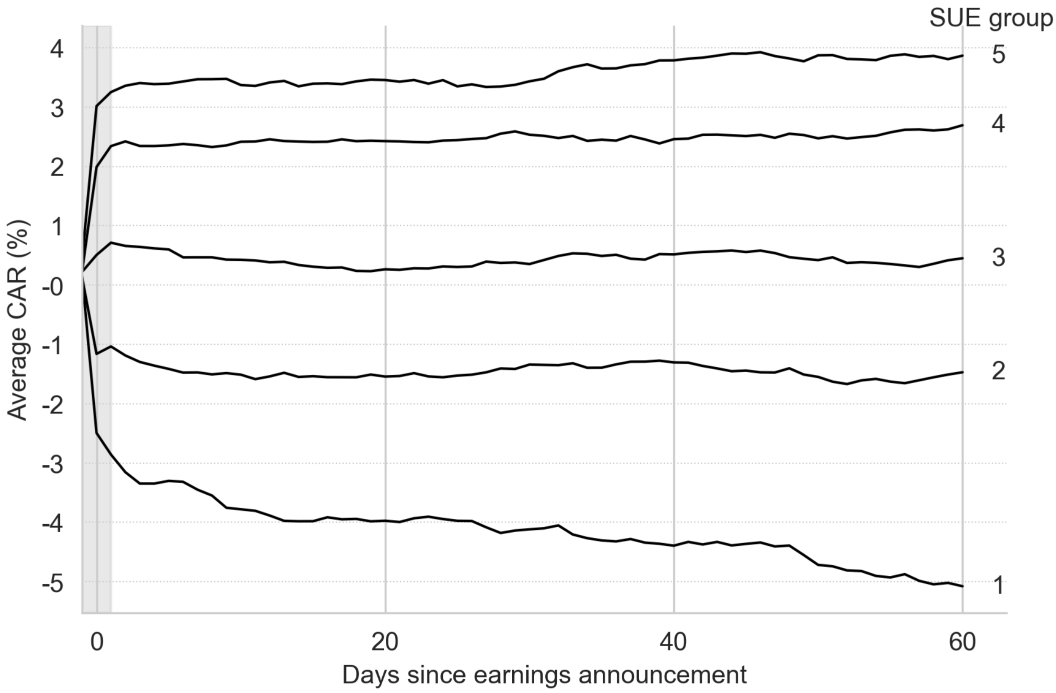

Figure 3: Average cumulative abnormal returns (CAR, %) across standardized unexpected earnings (SUE) quintile portfolios from day t=-1 to t=+60, where t=0 denotes the earnings announcement date. The grey area highlights the immediate return window.

We cautiously benchmark our findings against the two international studies discussed in Section 2.2.3 that also report daily event-time analysis of PEAD in Sweden.[15] Griffin et al. (2010) reports a 6-month PEAD drift of approximately 9% using buy-and-hold abnormal returns (BHAR). We note that their annualized return of 19% is substantially higher than ours at 11.8%, which may partially reflect the compounding nature of BHAR and the longer holding period used in their analysis. In their earlier working paper (Griffin et al., 2006), they show that the drift is primarily driven by the negative side of the strategy, a finding consistent with ours.

Hung et al. (2015) also use BHAR and report a 3-month PEAD drift of 5.54% for the 2001-2004 period and 1.91% for 2006-2009. Although they do not specify whether the drift arises primarily from the long or short leg of the strategy, our corresponding 3-month CAR of 2.83% falls within this range.

In Table 4 we sort firms on both earnings surprise (SUE) and level of information uncertainty, proxied by the inverse of firm size ($\frac{1}{MV}$), with smaller firms classified as having higher uncertainty. The drift is visualized in Figure 6 in Appendix E.

[15]While the methodology of BHAR and CAR slightly differs, we refer to Appendix D where we present BHAR results to illustrate the similarity, and hence the comparability.

Table 4: Cumulative Abnormal Returns (CARs) by SUE Quintiles and Uncertainty

SUE group	N	CAR(-1,1)	CAR(2,20)	CAR(21,40)	CAR(41,60)	CAR(2,60)
Panel A: High uncertainty						
High (5)	982	3.88%***	0.38%	0.20%	0.33%	0.91%*
		(0.0028)	(0.0031)	(0.0031)	(0.0034)	(0.0053)
4	918	2.75%***	0.17%	0.29%	0.48%	0.95%**
		(0.0022)	(0.0027)	(0.0029)	(0.003)	(0.0046)
3	878	1.14%***	-0.47%*	0.29%	-0.18%	-0.35%
		(0.0021)	(0.0027)	(0.0028)	(0.0032)	(0.005)
2	968	-0.51%**	-0.95%***	-0.02%	-0.37%	-1.34%***
		(0.0024)	(0.003)	(0.0028)	(0.0034)	(0.0051)
Low (1)	976	-3.13%***	-1.66%***	-0.28%	-1.45%***	-3.38%***
		(0.0025)	(0.0037)	(0.0035)	(0.004)	(0.0066)
PEAD HU		7.01%***	2.03%***	0.48%	1.77%***	4.29%***
		(0.0038)	(0.0048)	(0.0047)	(0.0052)	(0.0085)
Panel B: Low uncertainty						
High (5)	947	2.59%***	0.02%	0.47%**	-0.18%	0.31%
		(0.0022)	(0.0022)	(0.0024)	(0.0029)	(0.0043)
4	881	1.91%***	-0.01%	-0.24%	-0.03%	-0.27%
		(0.0019)	(0.002)	(0.0021)	(0.0023)	(0.0038)
3	847	0.28%	-0.43%**	0.21%	0.05%	-0.17%
		(0.0017)	(0.0017)	(0.0019)	(0.0022)	(0.0033)
2	931	-1.58%***	-0.05%	0.50%**	0.05%	0.50%
		(0.0019)	(0.002)	(0.0022)	(0.0024)	(0.0036)
Low (1)	942	-2.58%***	-0.56%**	-0.57%**	0.11%	-1.01%**
		(0.0024)	(0.0027)	(0.0028)	(0.0037)	(0.0051)
PEAD LU		5.17%***	0.58%*	1.03%***	-0.29%	1.33%**
		(0.0033)	(0.0035)	(0.0037)	(0.0047)	(0.0067)
Panel C: Comparing PEAD strategy in High uncertainty vs. Low uncertainty						
HU - LU		1.84%***	1.45%***	-0.55%	2.06%***	2.96%***
		(0.0050)	(0.0060)	(0.0060)	(0.0070)	(0.0108)

Average cumulative abnormal returns (CARs) for portfolios sorted by standardized unexpected earnings (SUE) quintiles across various event windows, where day 0 is the earnings announcement date. Panel A reports CARs for portfolios formed from high-uncertainty stocks, while Panel B reports CARs for low-uncertainty stocks. CARs are adjusted using benchmark portfolios matched on firm size and book-to-market ratio. Columns report CARs for the immediate window CAR(-1,1), the first month CAR(2,20), the second month CAR(21,40), the third month CAR(41,60), and the full quarter CAR(2,60). The "PEAD" row shows returns to a long-short strategy that takes a long position in the highest SUE quintile and a short position in the lowest. Standard errors are reported in parentheses, and two-sided p-values are used for significance testing. Panel C presents the Wald test comparing difference in CARs between the high- and low-uncertainty PEAD strategies (HU - LU). Standard errors are reported in parentheses, and one-sided p-values are used. Significance levels are indicated by: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

For high-uncertainty firms, PEAD is particularly strong where the high SUE portfolio generates a significant CAR(2,60) of 0.91%, while the low SUE portfolio shows a significantly negative return of -3.38%. The PEAD strategy generates a CAR(-1,1) of 7.01% and CAR(2,60) of 4.29%.

In contrast, the drift is substantially weaker among low-uncertainty firms. While announcement window returns (CAR(-1,1)) remain significant, the post-announcement drift is smaller and less consistent. The CAR(2,60) for the PEAD strategy is 1.33%, significant at the 5% level, and the return path shows weaker continuation beyond the first month. Furthermore, we observe a reversal in the third month, where the highest earnings surprise group exhibits negative abnormal returns, while the lowest earnings surprise group shows positive abnormal returns.

Panel C formally compares the PEAD strategy returns between the uncertainty portfolios. The difference in CAR(2,60) between high- and low-uncertainty firms is 2.96% and statistically significant at the 1% level. This supports the interpretation that information uncertainty, proxied by firm size, moderates the strength of the PEAD anomaly and supports our second hypothesis. These findings suggests that investors underreact more strongly to earnings news in firms with higher uncertainty, consistent with behavioral theories of difficulty in processing noisy signals.

Taken together, our event-time results support the view that the PEAD anomaly is at least partly driven by firm-level characteristics, particularly those related to the information environment, and persists even after adjusting for size and value as risk factors in the calculation of abnormal returns. These results and their implications are further investigated and discussed in the calendar-time analysis.

4.2 Calendar-Time Analysis

In Table 5, we find from the calendar-time regressions (CTRs) that the α for the highest earnings surprise (SUE5) and the PEAD portfolios are positive and significant at the 1% level in all models, indicating risk-adjusted abnormal returns for these portfolios. In contrast, the lowest earnings surprise portfolio (SUE1) does not have statistically significant α's. We find the monthly abnormal returns of the PEAD strategy (α_{PEAD}) to be 0.70% under the CAPM and 0.72% under the FF3 model, both significant at the 1% level. In the FFC4 model, where we introduce the momentum factor, the α is instead 0.56% and significant on the 5% level. Thus, we find support for our first hypothesis, namely the existence of PEAD in Sweden during the period 2005Q1 to 2023Q1.

The abnormal returns of the PEAD strategy are primarily driven by the long leg of the portfolio. Under the FFC4 model, the long portfolio generates a significant alpha of 0.62%, while the short portfolio generates an insignificant alpha of 0.06%. This suggests that a long-only strategy would be beneficial for the full-sample PEAD strategy.

Table 5: Calendar-Time Regressions on Full Sample

	SUE5 (Long)			SUE1 (Short)			PEAD		
	CAPM	FF3	FFC4	CAPM	FF3	FFC4	CAPM	FF3	FFC4
α	0.0072***	0.0067***	0.0062***	0.0001	-0.0005	0.0006	0.0070***	0.0072***	0.0056**
	(0.0026)	(0.0022)	(0.0021)	(0.0026)	(0.0020)	(0.0021)	(0.0023)	(0.0023)	(0.0023)
β	0.7016***	0.6973***	0.7158***	0.7515***	0.7451***	0.7046***	-0.0499	-0.0478	0.0112
	(0.0423)	(0.0322)	(0.0362)	(0.0720)	(0.0677)	(0.0513)	(0.0605)	(0.0625)	(0.0460)
s		0.6221***	0.6481***		0.8033***	0.7463***		-0.1812**	-0.0981
		(0.0645)	(0.0672)		(0.0866)	(0.0711)		(0.0760)	(0.0708)
h		-0.0083	0.0096		-0.0038	-0.0430		-0.0045	0.0526
		(0.0871)	(0.0857)		(0.0808)	(0.0823)		(0.1236)	(0.1174)
m			0.0506			-0.1109**			0.1615***
			(0.0315)			(0.0486)			(0.0458)
R^2	0.5779	0.6888	0.6924	0.5681	0.7264	0.7410	0.0083	0.0350	0.1377
R^2 *adj.*	0.5760	0.6845	0.6866	0.5661	0.7226	0.7362	0.0037	0.0216	0.1216
N	219	219	219	219	219	219	219	219	219

Full sample calendar-time regression results for the SUE5 (long), SUE1 (short), and PEAD trading strategies. Regressions are estimated using ordinary least squares (OLS) with Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors, and two-sided p-values are reported. The table reports alphas and factor loadings from the Capital Asset Pricing Model (CAPM), Fama-French 3-factor (FF3), and Fama-French-Carhart 4-factor (FFC4) models. α represents abnormal returns. β, s, h and m corresponds to the loadings on the market, size, value, and momentum factors. Standard errors are shown in parentheses. Significance levels are indicated by: ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

The factor loadings indicate substantial exposure to the market and size factors for the SUE5 and SUE1 portfolios. Furthermore, the SUE1 portfolio has a significant negative loading on the momentum factor. We observe that the PEAD portfolio has a negative and statistically significant loading on the size factor in the FF3 model, which becomes insignificant when the momentum factor is included in the FFC4 model. Furthermore, the loading on the momentum factor is positive and statistically significant, which is in line with both PEAD and momentum being short-term stock price continuation anomalies (Zhang, 2006). Furthermore, we note that the R^2 and adjusted R^2 range from 56% to 74% for the long and short portfolios, but are substantially lower for the PEAD portfolio. This suggests that the risk models explain little of the variation in its returns, which is consistent with the portfolio being designed to be market-neutral and its abnormal returns to not be captured by standard risk factors.

To the best of our knowledge, no prior study has examined PEAD using CTRs in Sweden over this sample period, consistent with the absence of CAR-based studies noted earlier. However, we cautiously benchmark our findings against the CTR results reported in Setterberg (2011). For the period 1990-2005, Setterberg (2011) reports a monthly alpha of 0.9% (11% annualized), driven by a long position return of 0.7% and a short position of -0.2%, after controlling for FF3 risk factors. Our results are broadly consistent, particularly in that abnormal returns are primarily found in the long leg of the PEAD strategy when examining it using CTR. However, we duly note the difference in time period, combined with the author's sample being restricted to A-list stocks (large-cap), which renders a comparison of magnitudes less meaningful. In relation to international research, we note that our FF3 risk-adjusted monthly abnormal return of 0.72% falls within the range of 0.593-0.773% presented in Section 2.2.3.

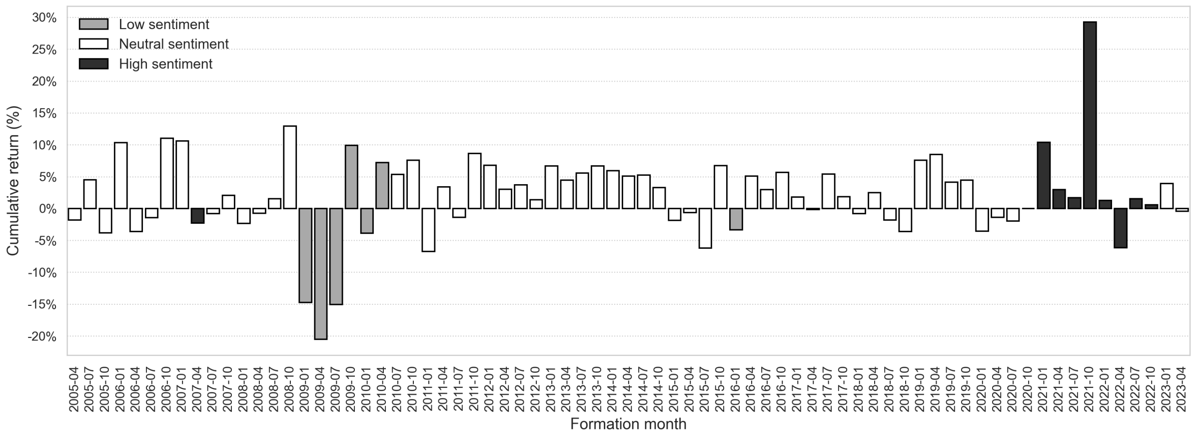

Figure 4: Cumulative 3-month returns (%, not risk-adjusted) from the PEAD trading strategy for each quarterly portfolio formation date from April 2005 to April 2023. Bar colors indicate the prevailing investor sentiment at the time of portfolio formation, categorized as low (white), neutral (gray), or high (black) based on the Baker & Wurgler sentiment index.

Figure 4 plots the cumulative return of the PEAD portfolio (not risk-adjusted) for each formation-date over the 3-month holding period. Here, we find by visual inspection that most quarters are neutral sentiment and generate positive PEAD returns. However, there are two major outlier periods: (i) a period of low sentiment post the global financial crisis in 2009 where we observe negative quarterly PEAD returns of approximately -15-20% for three quarters in a row, and (ii) a period of high sentiment post the Covid-19 fiscal stimulus in 2021 where we observe a quarterly PEAD return of approximately 30%.

In Table 6 Panel A, we observe that the long portfolio investing in high-uncertainty stocks generates a positive α of 0.90% after controlling for FFC4 risk factors which is significant on the 1% level whereas the short portfolio has a negative alpha of -0.21% that is not significant. The high-uncertainty PEAD strategy generates a monthly α of 1.11%, significant on the 1% level. In contrast, for the strategy investing in low-uncertainty stocks, the long position generates an alpha of 0.31%, the short position 0.32%, and the PEAD portfolio -0.01%; however, none of these α's are statistically significant.

Our results indicate that high-uncertainty stocks show stronger positive drift following positive earnings surprises, and more negative drift after negative surprises, compared with low-uncertainty stocks. Furthermore, we observe that the lowest SUE quintile in the low-uncertainty group generates a slightly positive α, potentially linked to the third-month reversal observed in Table 4. One possible explanation for this reversal, in line with Milian (2015), is that unsophisticated arbitrageurs may overreact to the earnings announcement, leading to a modest price reversal in the following months when the market corrects.

Since our proxy for information uncertainty is analogous with firm size, our finding of no significant drift in low-uncertainty stocks is interesting in light of Setterberg (2011) who reports a significant drift for large stocks in Sweden. This has two implications. First, the Swedish market seems to be have become relatively efficient to incorporate earnings information for larger firms where the signal in the earnings announcement is less uncertain. Second, the PEAD trading strategy in Sweden for more recent periods may be driven primarily by the drift in firms with higher information uncertainty.

In Table 6 Panel B, we report the result of the Wald test testing our second hypothesis. The difference in alphas is 1.12 percentage points, and the alpha of the high-uncertainty PEAD strategy is larger than that of the low-uncertainty PEAD strategy at the 1% significance level. This suggests that the PEAD strategy investing in high-uncertainty stocks generates higher abnormal returns compared to the PEAD strategy investing in low-uncertainty stocks, supporting our second hypothesis. Similar to our findings in the event-time analysis, this supports the notion that greater information uncertainty increases the time it takes for the market to interpret and incorporate earnings news into prices.

Table 6: Calendar-Time PEAD Strategies by Uncertainty, Controlling for FFC4

Panel A: Regression	High Uncertainty (HU)			Low Uncertainty (LU)		
	SUE5 (Long)	SUE1 (Short)	PEAD	SUE5 (Long)	SUE1 (Short)	PEAD
α	0.0090***	-0.0021	0.0111***	0.0031	0.0032	-0.0001
	(0.0027)	(0.0028)	(0.0033)	(0.0024)	(0.0021)	(0.0028)
β	0.7183***	0.6742***	0.0441	0.7160***	0.7376***	-0.0216
	(0.0444)	(0.0669)	(0.0636)	(0.0428)	(0.0520)	(0.0475)
s	0.8778***	0.9351***	-0.0572	0.4013***	0.5549***	-0.1536*
	(0.0838)	(0.1162)	(0.1098)	(0.0880)	(0.0883)	(0.0811)
h	-0.0927	-0.1559	0.0632	0.1224	0.0771	0.0453
	(0.0883)	(0.1410)	(0.1670)	(0.1160)	(0.0795)	(0.1129)
m	0.0452	-0.0944*	0.1395***	0.0576	-0.1274***	0.1850***
	(0.0416)	(0.0548)	(0.0498)	(0.0368)	(0.0483)	(0.0580)
R^2	0.6121	0.6360	0.0442	0.6259	0.7056	0.1532
R^2 *adj.*	0.6048	0.6292	0.0263	0.6189	0.7001	0.1374
N	219	219	219	219	219	219
Panel B: Wald test comparing PEAD strategies						
$\alpha_{HU} - \alpha_{LU}$			0.0112***			
			(0.0041)			

Panel A reports calendar-time regression results for the SUE5 (long), SUE1 (short), and PEAD trading strategies, with the sample divided between high-uncertainty (HU) and low-uncertainty (LU) stocks. Regressions are estimated using ordinary least squares (OLS) with Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors, and two-sided p-values are reported. The table reports alphas (α) and factor loadings from the Fama-French-Carhart 4-factor (FFC4) model. α represents abnormal returns. β, s, h and m correspond to the loadings on the market, size, value, and momentum factors. Standard errors are shown in parentheses. Panel B reports the results of a directional Wald test comparing PEAD strategy alphas between the HU and LU portfolios. The test is based on a seemingly unrelated regression (SUR) framework, and standard errors are shown in parentheses. One-sided p-values are reported. Significance levels are indicated by: $***p < 1\%$, $**p < 5\%$, $*p < 10\%$.

These findings are consistent with those of Jiang et al. (2005), Zhang (2006), Francis et al. (2007), and Gerard (2012), and have important implications for investors: the abnormal returns of a PEAD-based hedge strategy appears to be largely driven by the high-uncertainty stocks in the portfolio. Additionally, our use of market capitalization as a proxy aligns our findings with those of Martineau (2019), who document the disappearance of the drift among large U.S. firms in more recent periods.

In the first regression in Table 7, we include a dummy variable for high-sentiment periods. Its coefficient is positive but not statistically significant at conventional levels, indicating that although the abnormal return of the PEAD strategy appears to be higher during high-sentiment periods, no statistically reliable inference can be drawn.

Table 7: Dummy Regression for PEAD Sentiment Interaction, Controlling for FFC4

	High Sentiment (HS)	Low Sentiment (LS)	Combined
α	0.0049**	0.0077***	0.0073***
	(0.0022)	(0.0020)	(0.0019)
δ_{HS}	0.0050		0.0029
	(0.0093)		(0.0092)
δ_{LS}		-0.0223**	-0.0219**
		(0.0097)	(0.0097)
β	0.0118	0.0168	0.0171
	(0.0463)	(0.0424)	(0.0427)
s	-0.0954	-0.0843	-0.0830
	(0.0714)	(0.0677)	(0.0684)
h	0.0516	0.0477	0.0472
	(0.1178)	(0.1039)	(0.1044)
m	0.1606***	0.1498***	0.1494***
	(0.0455)	(0.0387)	(0.0387)
R^2	0.1398	0.1701	0.1707
R^2 *adj.*	0.1196	0.1506	0.1473
N	219	219	219

Calendar-time regression results for the PEAD strategy, controlling for the Fama-French-Carhart 4-factor (FFC4) model and incorporating interaction terms for investor sentiment. Regressions are estimated using ordinary least squares (OLS) with Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors, and two-sided p-values are reported. The regressions include dummy variables for high and low sentiment periods to assess differential performance of the PEAD strategy under varying sentiment conditions. Coefficients δ_{HS} and δ_{LS} capture the incremental return associated with high and low sentiment, respectively and relative to the baseline. α represents abnormal returns. β, s, h and m correspond to the loadings on the market, size, value, and momentum factors. Standard errors are shown in parentheses. Significance levels are indicated by: ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

In the second regression in Table 7, we include a dummy variable for periods of low sentiment and find its coefficient to be -0.0223 and statistically significant at the 5% level. Moreover, the regression alpha is higher than that of the baseline PEAD strategy reported in Figure 4. These results suggest that the strategy generates positive abnormal monthly returns of 0.77% during periods of neutral or high sentiment, but negative abnormal returns of -1.46%[16] during periods of low sentiment. This suggests that the abnormal return of the PEAD strategy is not only decreasing, but actually reversing, during periods of low sentiment. In other words, an investor could potentially benefit from a reversed PEAD strategy with a long position in negative earnings surprise firms and a short position in positive earnings surprise firms. While this may seem counterintuitive, a behavioral interpretation is that investors overreact to bad news during low sentiment, which leads to a subsequent market correction and positive alpha of the short position. However, implementing this strategy, i.e., to take a long position in low SUE stocks and

[16] 0.0077 + (-0.0223) = -0.0146.

a short position in high SUE stocks, would no longer be the traditional PEAD strategy, but rather imply speculating on a market overreaction.

In the combined model in Table 7, where both dummy variables are included simultaneously, the coefficient for high sentiment remains positive but insignificant, while the coefficient for low sentiment remains negative and significant at the 5% level. These results indicate that the PEAD strategy's abnormal returns are reduced during periods of low investor sentiment, while high sentiment does not have a significant association. Consequently, we do not find support for Hypothesis 3.1, but we do find support for Hypothesis 3.2. Hence, our study aligns with previous studies identifying a relation between investor sentiment and PEAD, such as Mian and Sankaraguruswamy (2012) and Livnat and Petrovits (2019).

Similar to the findings of Stambaugh et al. (2012) for other anomaly-based trading strategies, we find that the profitability of a PEAD-based strategy is higher in periods of higher sentiment compared with periods of lower sentiment. Our findings indicate that a selective PEAD strategy that avoids low sentiment periods could generate higher abnormal returns than implementing the PEAD strategy over all periods.

Based on our findings that the abnormal return of the PEAD portfolio is primarily driven by high-uncertainty stocks, and that the performance of the PEAD strategy diminishes during periods of low investor sentiment, we propose a selective PEAD strategy that incorporates these insights and pursues uncertainty while "skipping the dip". Specifically, this portfolio follows the high-uncertainty PEAD strategy when investor sentiment is neutral or high, but allocates to the risk-free asset[17] when sentiment is low.

In Table 8 Panel A we present the results of the FFC4-adjusted CTRs for the long portfolio (SUE5), the short portfolio (SUE1), and the PEAD hedge portfolio for the selective strategy. Furthermore, we include the PEAD strategy for the full sample, initially presented in Table 5, for comparison. We find that the long position has a positive alpha of 0.61% significant on the 10% level while the short position has a negative alpha of -0.62% significant on the 5% level. The selective PEAD strategy generates monthly abnormal returns of 1.23% that is statistically significant on the 1% level. In terms of factor exposures, we note that the selective strategy exhibits a lower and less statistically significant loading on the momentum factor compared to the full-sample PEAD strategy. This, together with a substantially lower R^2, suggests that the selective strategy is explained to a lower degree by the included risk factors.

In Panel B, we present the Wald test which formally tests our fourth hypothesis, namely if the return of the selective PEAD strategy is higher than the return of the full-sample PEAD strategy. The difference in alphas is 0.67 percentage points, and the alpha of the selective strategy is higher than that of the regular PEAD strategy at the 1% significance level. This suggests that the selective PEAD generates higher abnormal returns compared with the full-sample PEAD strategy, supporting our fourth hypothesis.

[17] Thus generating 0% excess return.

Hence, an investor implementing the PEAD strategy could benefit from only investing in high-uncertainty stocks and avoiding the strategy in periods of low sentiment.

Table 8: Selective Strategy vs. Standard PEAD Strategy, Controlling for FFC4

Panel A: Regression	Selective			Full Sample
	SUE5 (Long)	SUE1 (Short)	PEAD	PEAD
α	0.0061*	-0.0062**	0.0123***	0.0056**
	(0.0032)	(0.0028)	(0.0030)	(0.0023)
β	0.6425***	0.5700***	0.0726	0.0112
	(0.0557)	(0.0610)	(0.0550)	(0.0460)
s	0.7087***	0.6714***	0.0372	-0.0981
	(0.1242)	(0.1043)	(0.0819)	(0.0708)
h	-0.0740	-0.1002	0.0262	0.0526
	(0.1036)	(0.1038)	(0.1328)	(0.1174)
m	0.1110**	0.0156	0.0954**	0.1615***
	(0.0502)	(0.0515)	(0.0445)	(0.0458)
R^2	0.4998	0.5355	0.0231	0.1377
R^2 *adj.*	0.4904	0.5268	0.0048	0.1216
N	219	219	219	219
Panel B: Wald test comparing PEAD strategies				
$\alpha_{Selective} - \alpha_{FullSample}$			0.0067***	
			(0.0025)	

Comparison of calendar-time regression results for selective strategies versus the full sample. Panel A reports regression results for the selective SUE5 (long), SUE1 (short), and PEAD trading strategies, as well as the PEAD strategy using the full sample. Regressions are estimated using ordinary least squares (OLS) with Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors, and two-sided p-values are reported. The table reports alphas and factor loadings from the Fama-French-Carhart 4-factor (FFC4) model. α represents abnormal returns. β, s, h and m correspond loadings on the market, size, value, and momentum factors. Standard errors are shown in parentheses. Panel B reports the results of a directional Wald test comparing PEAD strategy alphas between the selective strategy and the full sample. The test is based on a seemingly unrelated regression (SUR) framework. Standard errors are shown in parentheses. One-sided p-values are reported. Significance levels are indicated by: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$.

Comparing the results of Table 5, Table 6, and Table 8, we find the α to be close to zero for the full-sample short position, slightly more negative for the high-uncertainty portfolio, and even more negative and statistically significant on the 5% level for the selective strategy. With the perspective of limits to short selling, one would expect the α to be crowded out if short selling is possible. However, for the selective strategy, we find that the abnormal returns are generated approximately equally from the long- and short positions. If restrictions on short sales is the main cause of the drift, following the argument related to transaction costs in Bernard and Thomas (1989), we would have predicted the short leg to provide the majority of the drift. This indicates three implications: (i) In line with the findings by Diether et al. (2002) that short selling constraints are more pronounced in smaller and less liquid stocks, stocks with higher uncertainty appear more difficult to short. (ii) Shorting is even more difficult, or investors refrain from shorting and selling stocks in general, during periods of neutral and high sentiment in line with the literature as presented in Section 2.3.4 that investors are more optimistic in such periods compared with periods of low sentiment. (iii) However, short-sale constraints do not appear to be the primary explanation of the drift since the short position does not constitute the majority of the drift, in line with the findings of Bernard and Thomas (1989).

4.3 Robustness Checks and Reliability of Assumptions

To test the robustness of our findings related to the presence of PEAD in the Swedish market (Hypothesis 1) as well as the higher returns of our selective PEAD strategy (Hypothesis 4), we re-estimate the FFC4 risk-adjusted α for both the full sample and the selective strategies, and conduct the Wald test comparing the two. The robustness checks are conducted by varying one key assumption at a time and the resulting estimates are reported in Table 9. We follow the same methodology as in Table 8, and report the relevant figures of the main analysis in Panel A for comparison.

In Panel B, we demonstrate the robustness of our results with respect to the earnings surprise proxy (SUE) by modifying the components of its construction, as defined in Equation 1. First, we replace the denominator with the stock price on the last trading day of the month preceding the earnings announcement (SUE_{price}). Second, we modify the numerator by calculating unexpected earnings based on the average of analyst forecasts instead of the median (SUE_{avg}). In both cases, the full-sample strategy continues to generate a positive and statistically significant α, and the selective strategy consistently outperforms the full sample.

In Panel C, we demonstrate that our results are robust to the choice of uncertainty proxy. First, we use the inverse of the number of analysts providing an estimate ($\frac{1}{COV}$). While the results continue to support our hypotheses, the relative performance of the selective strategy appears somewhat weaker under this specification. A plausible explanation is that analyst coverage is a discrete variable, which may limit its ability to meaningfully differentiate between firms with the same level of coverage.[18] Second, we find that stock volatility ($SIGMA$), defined as the volatility of weekly excess returns over the 52 weeks preceding the earnings announcement, generates results similar to those of our main analysis. Third, we use the dispersion of analyst forecasts ($DISP$). Although we find that the selective strategy generates higher abnormal return than the full-sample PEAD, neither of the alphas nor the Wald test are significant. This may be due to the high number of firms covered by only one analyst, which leads to a loss of approximately

[18]For example, between two firms both covered by only one analyst.

1/3 of the sample when using this proxy, thereby limiting statistical inference.

Table 9: Robustness Checks

	FFC4 Adjusted Calendar-Time Regression		Wald Test
	$\alpha_{Selective}$	$\alpha_{FullSample}$	$\alpha_{Selective} - \alpha_{FullSample}$
Panel A: Benchmark			
	0.0123***	0.0056**	0.0067***
	(0.0030)	(0.0023)	(0.0025)
Panel B: Varying SUE Proxy			
SUE_{price}	0.0103***	0.0050**	0.0053***
	(0.0033)	(0.0023)	(0.0023)
SUE_{avg}	0.0123***	0.0047**	0.0076***
	(0.0029)	(0.0023)	(0.0024)
Panel C: Varying Uncertainty Proxy			
$\frac{1}{COV}$	0.0090***	0.0056**	0.0035**
	(0.0024)	(0.0023)	(0.0020)
$SIGMA$	0.0100***	0.0057**	0.0044**
	(0.0030)	(0.0023)	(0.0025)
$DISP$	0.0046	0.0021	0.0025
	(0.0036)	(0.0027)	(0.0029)
Panel D: Varying minimum firm size cutoffs			
100 MSEK	0.0131***	0.0057**	0.0074***
	(0.0030)	(0.0023)	(0.0024)
500 MSEK	0.0137***	0.0072***	0.0065***
	(0.0032)	(0.0022)	(0.0023)
1,000 MSEK	0.0095***	0.0041*	0.0053***
	(0.0029)	(0.0022)	(0.0021)
Panel F: Varying Time Periods			
Pre 2014	0.0119***	0.0019	0.0100***
	(0.0038)	(0.0037)	(0.0039)
Post 2014	0.0121***	0.0078***	0.0043**
	(0.0045)	(0.0026)	(0.0026)

This table shows robustness checks for the Fama-French-Carhart 4-factor (FFC4) adjusted calendar-time regression results. The table reports estimated alphas for selective and full-sample PEAD strategies across a range of alternative specifications, along with Wald tests of the alpha differential. Panel A presents the benchmark result. Panels B-F report results under varying SUE proxies, uncertainty proxies, minimum firm size, and time periods. All regressions are estimated using ordinary least squares (OLS) with Newey-West heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. Only the estimated alphas and their standard errors are reported for the regressions. The Wald test is based on a seemingly unrelated regression (SUR) framework. P-values are two-sided for the regressions and one-sided for the Wald test. Standard errors are shown in parentheses. Significance levels are indicated by: ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

In Panel D, we show that our results are not dependent on the smallest firms in our sample by introducing a minimum market capitalization for firms included in the analysis.

While our main findings remain robust for all limits, we also observe that the performance of both the selective strategy and the full-sample PEAD strategy declines when the minimum size threshold is raised from 500 MSEK to 1,000 MSEK. This suggests that a non-negligible portion of the drift is attributable to firms with a market capitalization in this range.

In Panel E, we illustrate that our results are consistent over time. We find that the selective strategy outperforms the full-sample strategy in both periods. However, we also note that the full-sample PEAD strategy did not generate significant abnormal returns in the pre-2014 period. One possible explanation for this is the inclusion of the post-Global Financial Crisis period, which was characterized by persistently low investor sentiment, potentially decreasing the return in the total pre-2014 period.

The robustness checks confirm our findings, that PEAD persisted in Sweden during our sample period and that the magnitude is conditional on information uncertainty and investor sentiment, are consistent across a wide range of methodological choices.[19]

4.4 The Effects of Information Uncertainty

Similar to Zhang (2006), we use the inverse of market capitalization ($\frac{1}{MV}$) as our main proxy for information uncertainty and include 3 of the 5 additional proxies in our robustness checks. We do not examine the remaining 2 potential proxies, firm age and the volatility of cash flow from operations, as incorporating them would require additional datasets. To theoretically justify these measures, we start by considering the information signal and its related uncertainty, and why it differs from "information risk".

In relation to the definition of uncertainty and the model by Holthausen and Verrecchia (1988) presented in Section 2.3.3, we define the "event" as the positive or negative signal from the earnings surprise, measured by the standardized unexpected earnings. The outcome of the event is the theoretical value of the information content of the signal to be priced into the stock. While this can be estimated to some degree, the outcome is unknown ex ante. The same applies for the distribution of potential outcomes. Thus, the event is uncertain rather than risky.

As an illustrative example, consider drawing from a deck of cards. If one knows that the deck is complete and randomly ordered, the probability of drawing the queen of hearts is known to be 1/52. Hence, as the distribution of outcomes is known, the event is risky. However, if the deck is not orderly assigned, but rather compiled of 100 random cards from an unknown amount of decks, such conclusions would be impossible. Thus, as the distribution of outcomes is not known, the event is labeled uncertain. The same logic applies to our definition of unexpected earnings.

Say a firm is followed by two analysts. One estimates next quarter's EPS to be 1, and the other 2. Later, the firm reports an EPS of 4. In this example, we get

[19] Additional robustness checks are presented in Table 11 in Appendix F.

unexpected earnings (UE) of 2.5 and standardized unexpected earnings (SUE) of 0.625. The implication of this signal for the stock price may then be estimated through valuation methods, but one cannot know for certain what the outcome will be since it will depend on assumptions and confounding factors. Rather, it will be an estimate where the true price impact is unknown, same as one cannot know what card will be drawn from the deck. Considering the distribution of the potential price impact, one may set certain boundaries. In this example, the theoretical price impact would likely be positive and within some range of realistic values inferred from the marginal increase in earnings. Thus, an informed guess can be made. However, the distribution is not *known* in the same sense that one *knows* that a standard deck of cards has 13 ranks in 4 suits to draw from.

To proxy the ex ante earnings expectations, we adopt analyst estimates. Although the rationality of such forecasts is debated as they may exhibit bias (Lim, 2001), such bias is also exhibited by the aggregate market. Therefore, biased forecasts are not a primary concern since we want to measure how the market interprets and subsequently responds to the earnings signal and assume analysts are to some degree representative of the market. Rather, the biases, and other factors in the behavioral finance framework influencing agents in the market, are precisely what we aim to capture with our measure of information uncertainty.

Now that the event is defined and attributed to uncertainty rather than risk, we consider the "ideal" theoretical proxy to be used for information uncertainty, i.e., the degree to which the market is uncertain about the implication of an earnings surprise. Effectively, a higher degree of uncertainty means that the signal is difficult to value. Logically, and in accordance with the two factors for price change in the Holthausen and Verrecchia (1988) model, this may be either (i) because the signal is not clear, or (ii) because the interpretation or translation of the signal is difficult. First, an unclear signal would be associated with how strongly the market believes the median analyst forecast truly represents the ex ante expectations. We relate this difficulty to $DISP$ and COV. Second, difficulties in the interpretation of a signal would be related to the information available to relate to said signal when conducting the valuation. We relate this to MV and $SIGMA$.

Considering analyst coverage (COV), it has a critical issue in the form of limited granularity. Since the variable is discrete, no distinction can be made regarding which stocks have high or low uncertainty within a given number of analysts. Furthermore, if one adopts the view that uncertainty in the signal arises from underlying firm characteristics, analyst coverage may be a flawed proxy. Specifically, it may be biased for high-status firms that attract greater analyst attention for reasons exogenous to their actual level of information uncertainty. With this in mind, we do not use COV as our main proxy for information uncertainty.

As discussed in Section 3.6, for roughly 1/3 of our sample the number of analysts covering the firm (COV) is 1, which results in $DISP$ being undefined. Furthermore, lower coverage is associated with higher uncertainty. Thus, using $DISP$ would not only reduce our sample size but also systematically exclude firms with limited analyst coverage, i.e., those with higher information uncertainty. Given these limitations, we do not employ $DISP$ as our primary proxy for information uncertainty.

Zhang (2006) argues that small firms are more uncertain since they are likely less diversified, have less market-available information, fewer stakeholders, and may bear less disclosure costs. Conversely, investors and analysts may have fixed costs of acquiring information. The relation between firm size and information uncertainty is also found empirically (Lim, 2001; Zhang, 2006). The inverse of firm size ($\frac{1}{MV}$) may therefore be used as a simple yet sound proxy with the benefits of not limiting our sample data and providing a high degree of granularity. Furthermore, as a robustness check following Zhang (2006), we add excess stock return volatility ($SIGMA$) as an additional measure of information uncertainty which shares the benefits of being a continuous variable and not materially limiting our sample data. However, this is not our main proxy since it may be more related to general difficulties in valuation, rather than the difficulty to implement the earning surprise.

Thus, to allow for a larger sample, higher granularity, and stronger economic intuition, we opt for market capitalization as our main proxy. We are cognizant that this measure likely also captures aspects other than uncertainty. However, since we control for size as a risk factor, through adjusting for size portfolios in the event-time analysis and including size as a risk factor in the calendar-time analysis, we attribute the remaining effects to something other than risk. While the specific effects related to uncertainty are difficult to prove[20], our results and robustness checks using 3 additional proxies favor our interpretation of it being a sensible proxy for information uncertainty.

4.5 The Effects of Investor Sentiment

In relation to behavioral finance theory (Section 2.3.2) and the literature related to investor sentiment (Section 2.3.4), our study connects the profitability of the PEAD strategy to investor sentiment. This implies that by measuring and adjusting for the level of investor sentiment through the Baker-Wurgler index, an investor can limit periods of lower returns in the PEAD strategy by avoiding periods of low sentiment. Our result reconciles the PEAD anomaly with other anomaly-based trading strategies examined by Stambaugh et al. (2012) that show higher profitability in periods of higher sentiment.

Although our results related to investor sentiment are not directly comparable with previous literature, sentiment is by definition a time-varying state variable, which makes our findings broadly comparable to studies that distinguish between different time periods. As mentioned in Section 2.2.3, Hung et al. (2015) reports 3-month BHAR returns

[20]Where market capitalization may still be considered a proxy for something else, such as various aspects of limits to arbitrage. See further discussion in Section 2.3.1.

in the Swedish market of 5.54% during 2001-2004 and 1.91% during 2006-2009. Notably, the period with lower PEAD coincides with the low-sentiment period in 2009 following the Global Financial Crisis during which we also observe weak PEAD (see Figure 4). In contrast, their higher PEAD return corresponds to a period characterized by predominantly high or neutral sentiment.[21] Thus, while their results for the Swedish market are not presented with enough detail for any conclusions, this supports a time-varying aspect of PEAD potentially related to the prevailing investor sentiment.

While we regard the index developed by Baker and Wurgler (2006) as a sound proxy for the behavioral biases related to investor sentiment, we are cognizant that the time-varying states may be correlated with other underlying factors. Other potential proxies could be e.g., market returns as used in Bird and Yeung (2012); Bird et al. (2014) or something entirely different such as the cyclically adjusted price-to-earnings ratio (CAPE index) as developed by John Campbell and Robert Shiller (Campbell and Shiller, 1988a,b, 1998). However, to remain within the behavioral framework, we leave such robustness tests for further research.

Since our sample period spans from 2005 to 2023, it effectively captures only one major episode of low sentiment and one of high sentiment. This limitation could be addressed in future research, either practically, by awaiting new periods of high and low sentiment, or methodologically, by examining the PEAD anomaly in Sweden using alternative approaches such as earnings announcement returns which could expand the sample period backwards.

4.6 Trading Strategies and Limits to Arbitrage

Our normative decision rule, as concluded in Section 4.2, is to selectively implement the PEAD strategy by pursuing high-uncertainty stocks while avoiding periods of low sentiment. How then may this be implemented in practice? We propose two broad paths to follow: (i) the "hedge-portfolio" investor, and (ii) the "long-only" investor.

Practically, a hedge portfolio with zero net invested position would balance a long and a short position and offload after 3 months. As seen in Table 2, this portfolio would consist of approximately 25 stocks in our sample period.[22] Since no net position is involved for the hedge portfolio, a low sentiment period simply implies taking no action.[23] While this may sound simple considering the low volume, investors may face limits to arbitrage as discussed in Section 2.3.1. To illustrate the implementability, we consider the limited free float in SEK terms, transaction costs, and borrowing fees, assumed to be the primary trading frictions for the investor.

[21] According to our sentiment classification, the portfolio formation quarters in 2001-2004 are: 5 High, 8 Neutral, and 3 Low.

[22] Based on the median number of stocks of 13 and 12 for the SU5 high uncertainty and SUE1 low uncertainty respectively.

[23] In the analysis, we assume a passive investment in the risk-free rate during periods of low sentiment generating 0% excess return.

In terms of available equity, we refer to Table 2 where we observe that the firm size in the high-uncertainty long portfolio ranges 39 to 37,598 MSEK with a median of 1,872. Correspondingly for the short portfolio, firm size ranges between 39 and 18,118 MSEK with a median of 1,018. A large institutional investor attempting this strategy may thus be constrained to generate sufficient return in SEK terms, even though the abnormal return in percentage terms is high. This limitation is further compounded by the strategy's use of an equally-weighted portfolio, which implies that the maximum amount to invest is constrained by the available equity of the smallest firm in the portfolio. However, as shown in our robustness checks, the strategy has similar profitability when restricting the sample to firms with a market capitalization above 500 MSEK. Hence, assuming that a position of 0.5% of the total equity is feasible without materially impacting the price, the strategy could theoretically sustain a 62.5 MSEK gross investment.[24]

While the actual transaction costs will be dependent on the broker and investor, we present an assumption based on the research of Hagströmer (2023) who suggests that the bid-ask spread can constitute more than double the amount of commissions for small-cap Swedish stocks for retail investors. In our sample, the average bid-ask spreads is 1.20% for the short portfolio and 0.97% for the long portfolio the first trading day after the portfolio formation date.[25] We thus assume one-way total transaction costs ranging 100-200bps.

For borrowing-fees, we acknowledge that this will be more difficult to estimate as it will depend not only on the investor, but also on stocks' characteristics and short interest. However, using our findings and assumptions, we back out the maximum yearly borrowing fee to sustain a positive net alpha. Suppose a hedge fund takes a 50 MSEK total position in this strategy and earns Carhart (1997) gross nominal abnormal returns of approximately 8 MSEK.[26] It would then be burdened with transaction costs of approximately 4-8 MSEK.[27] Following this back-of-the-envelope calculation, we find that for net abnormal returns to remain positive, additional short-selling fees may not exceed 16% when transaction costs are 100bps, and 0% when transaction costs are 200bps. Furthermore, we are cognizant that very small firms with low liquidity may have less availability for short-selling (Diether et al., 2009), potentially placing a further restriction on the practical implementation of the hedge strategy. Based on this reasoning, we acknowledge that the net profitability of our selective strategy in nominal terms may be negligible and the hedge-portfolio strategy may be hard to implement, pointing towards the market being more efficient in the semi-strong form than implied by the gross α.

The long-only investor would eschew the short position and only take a long position in the portfolio formed on the stocks with the highest earnings surprises. Comparing

[24] 500 MSEK * 0.5% available equity * 25 firms = 62.5 MSEK.

[25] This can be benchmarked against Hagströmer (2023) who find bid-ask spreads of 9.2bps for large stocks, 41.9bps for mid-sized companies, and 84.3 for small stocks in the Nordics.

[26] 15.8% * 50 MSEK $\approx$ 8 MSEK.

[27] Assuming 2 one-way transaction per quarter per portfolio, transaction costs of 100-200bps, conservative 100% portfolio turnover each quarter, and no changes in value for simplicity.

the results in Table 6 and Table 8, we observe that avoiding periods of low sentiment appears less critical, as the full-sample high-uncertainty long position yields a higher monthly α of 0.90% compared to 0.61% for the selective strategy's long position. While this is somewhat counter-intuitive related to the behavioral theories, we note that it is in line with the findings of Livnat and Petrovits (2019) who found that high SUE stocks generate higher returns following periods of low sentiment than following periods of high sentiment. However, we note that the maximum investable amount for the long position will be constrained to half of the hedge-portfolio. With the same assumption of 100-200bps in transaction costs, the net α of the high-uncertainty strategy results in -5% to 3% i.e., not strictly positive. This further strengthens the conclusion from the hedge strategy that even though it generates a yearly gross α of 11.4%, the anomaly may not be sustained post practical trading frictions.

Based on these illustrative examples of how trading frictions may affect both hedge portfolio and long-only investors in a PEAD strategy with promising gross returns, an interesting avenue for future research would be to test the validity of our assumptions and examine the net profitability.

5. Conclusion

In this thesis, we identify PEAD in Sweden, find that it is concentrated to smaller firms, and that its magnitude is associated with information uncertainty and time-varying investor sentiment. Specifically, the drift is stronger for firms with higher uncertainty and when avoiding periods of low sentiment. This constitutes the basis for our normative recommendation of a preferable PEAD investment strategy generating 1.23% gross monthly abnormal return (15.8% annualized) after controlling for market, size, value, and momentum as risk factors. We find our identification of PEAD as well as the superior return of our selective strategy to be robust to varying the critical assumptions of our methodology.

Given our conclusion that the PEAD strategy has a significant association with state-dependent variations in investor sentiment, future research could extend our findings to include more periods of high and low sentiment to test if our findings remain robust, but also investigate whether some other time-varying factor could better explain the drift.

The main limitation of this thesis is that abnormal returns are calculated without accounting for transaction costs and short-selling constraints. In our discussion, we approximate the impact of such frictions and conclude that the net abnormal return may not be strictly positive. Coupled with the findings that PEAD is concentrated to smaller stocks, the feasibility of a practical implementation may be limited. Future research could examine the more precise impact of such frictions and investigate whether the anomaly can thus be reconciled with the semi-strong form of EMH.

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Appendix

A. Creation of Daily Portfolio Returns and FFC4-Factors

As no daily Swedish risk factors is found for our sample period, we re-construct these using all cleaned FinBas data retrieved[28] and follow the methodology of Sodini et al. (2022).

For the Fama-French 3-factor portfolios, we assign each observation to one of six portfolios based on the Book-To-Market ratio (BTM) as of the last of December, and the Size (MV) as of the last of June. The portfolio is constructed on the last of June and the portfolio weights are held constant for the following year. The breakpoint for Size is the 80^{th} percentile market value whereas the breakpoints for Book-to-Market are the 30^{th} and 70^{th} percentiles. The value-weighted daily portfolio returns for the 6 portfolios presented Figure 5 are used in the calculation of the factor-adjusted abnormal return for the CAR analysis as described in Section 3.4.

	80th Percentile MV	
	Small Value (SV)	Big Value (BV)
70th Percentile BTM		
	Small Neutral (SN)	Big Neutral (BN)
30rd Percentile BTM		
	Small Growth (SG)	Big Growth (BG)

Figure 5: Illustration of bi-variate portfolio sort with breakpoints.

To calculate the momentum factor, we first estimate the one-year return, defined as the percentage change in stock price from the last day of 12 months prior to the last day of one month prior to the measurement date. We then rank all stocks based on their one-year returns and classify them into three groups: winners, losers, and middle. The winners are the top 10% of stocks with the highest one-year returns, while the losers are the bottom 10% with the lowest one-year returns. This portfolio assignment is updated for each month and portfolio weights are held constant for the following month, during which the daily value-weighted return for the winners and losers portfolios are calculated.

To construct the daily factors for Small-Minus-Big (SMB), High-Minus-Low (HML) and Up-Minus-Down (UMD), we use the following equations:

$$SMB_t = \frac{R_{SV,t} + R_{SN,t} + R_{SG,t}}{3} - \frac{R_{BV,t} + R_{BN,t} + R_{BG,t}}{3} \tag{11}$$

$$HML_t = \frac{R_{SV,t} + R_{BV,t}}{2} - \frac{R_{SG,t} + R_{BG,t}}{2} \tag{12}$$

$$UMD_t = R_{winners,t} - R_{losers,t} \tag{13}$$

These daily factors are then aggregated into monthly factors by compounding:

[28] I.e., not only for those firms that were matched with the IBES dataset and used in the main analysis.

$$SMB_m = \prod_{t \in m} (1 + SMB_t) - 1 \tag{14}$$

$$HML_m = \prod_{t \in m} (1 + HML_t) - 1 \tag{15}$$

$$UMD_m = \prod_{t \in m} (1 + UMD_t) - 1 \tag{16}$$

These monthly factors are used in the Calendar-Time Regressions as described in Section 3.5.

B. Further Details of the CAR Methodology

To calculate the average Cumulative Abnormal Return for each portfolio presented in Section 3.2, we use the equally weighted average formula:

$$CAR_p(t_0, t_1) = \frac{1}{N_p} \sum_{i \in p} CAR_i(t_0, t_1) \tag{17}$$

For the one-sample t-test to assess whether the CAR for a given portfolio and event window is statistically different from zero ($E[CAR_p] = 0$), the test statistic is defined as:

$$t = \sqrt{N_p} \cdot \frac{CAR_p}{S_p} \quad \text{with} \quad S_p^2 = \frac{1}{N_p - 1} \sum_{i \in p} (CAR_i - CAR_p)^2 \tag{18}$$

where N_p is the number of events in portfolio p, CAR_i is the cumulative abnormal return for event i, and CAR_p is the average cumulative abnormal return for portfolio p. The statistic is assumed to follow a t-distribution with $N_p - 1$ degrees of freedom.

In the independent two-sample Welch's t-test, used to test the first hypothesis, i.e., if the CARs for the PEAD strategy is statistically different from 0, the test statistic is defined as:

$$t = \frac{PEAD}{S_{PEAD}} \quad \text{with} \quad S_{PEAD}^2 = \frac{S_{SUE5}^2}{N_{SUE5}} + \frac{S_{SUE1}^2}{N_{SUE1}} \tag{19}$$

where S_{SUE5}^2 and S_{SUE1}^2 are the sample variances of CARs in each group as defined in Equation 18, and N_{SUE5} and N_{SUE1} are the number of events within each portfolio. The test statistic is assumed to follow a t-distribution with degrees of freedom calculated as:

$$\nu = \frac{\left(\frac{S_{SUE5}^2}{N_{SUE5}} + \frac{S_{SUE1}^2}{N_{SUE1}} \right)^2}{\frac{(S_{SUE5}^2 / N_{SUE5})^2}{N_{SUE5} - 1} + \frac{(S_{SUE1}^2 / N_{SUE1})^2}{N_{SUE1} - 1}} \tag{20}$$

For the Wald test used to test our second hypothesis, i.e, if the CAR of the PEAD portfolio investing only in high-uncertainty firms is higher than the one that invest in low-uncertainty firms, the test statistic is assumed to follow a standard normal distribution and is defined as:

$$W = \frac{PEAD_{HU} - PEAD_{LU}}{\sqrt{SE_{HU}^2 + SE_{LU}^2}} \tag{21}$$

C. Further Details of the CTR Methodology

In the Seemingly Unrelated Regression (SUR) methodology, the individual regressions are stacked to form a system of equations that are solved jointly. This methodology is used to test both hypothesis 2 and 4 in the CTR framework and are here illustrated for hypothesis 2. To simplify, we consider the regressions in vector form, abstracting from the time index. Rewriting Equation 9 in this form yields:

$$R_p = X_p \beta_p + \varepsilon_p \tag{22}$$

We then stack the two regressions to form a system of equations that can be estimated jointly and take the following form in the case of the high-uncertainty (HU) and low-uncertainty (LU) PEAD portfolios used to test hypothesis 2:

$$\begin{bmatrix} R_{HU} \\ R_{LU} \end{bmatrix} = \begin{bmatrix} X_{HU} & 0 \\ 0 & X_{LU} \end{bmatrix} \begin{bmatrix} \beta_{HU} \\ \beta_{LU} \end{bmatrix} + \begin{bmatrix} \varepsilon_{HU} \\ \varepsilon_{LU} \end{bmatrix} \tag{23}$$

When solving this system of equations, we retrieve the covariance matrix of the estimated coefficients across the different regressions, enabling joint statistical inference and hypothesis testing. The test statistic used in the Wald test to compare the performance difference for the high- and low-uncertainty portfolios is defined as:

$$Z = \frac{\alpha_{HU} - \alpha_{LU}}{\sigma_\Delta} \quad \text{with} \quad \sigma_\Delta^2 = \operatorname{Var}(\alpha_{HU}) + \operatorname{Var}(\alpha_{LU}) - 2\operatorname{Cov}(\alpha_{HU}, \alpha_{LU}) \tag{24}$$

Here, α_{HU} and α_{LU} denote the estimated monthly abnormal returns for portfolios formed on high- and low-uncertainty stocks, respectively. The variances and covariance of the alpha estimates are extracted from the SUR model. The test statistic Z is assumed to follow a standard normal distribution.

D. BHAR Methodology and Results

To test the validity of comparing our CAR analysis with other studies using BHAR, we re-estimate the main event-time analysis using BHAR instead of CAR, where instead of using Equation 3, abnormal returns over a period is calculated using the formula:

$$BHAR_i(t_0, t_1) = \prod_{t=t_0}^{t_q}(1 + R_{i,t}) - \prod_{t=t_0}^{t_1}(1 + E[R_{i,t}]) \tag{25}$$

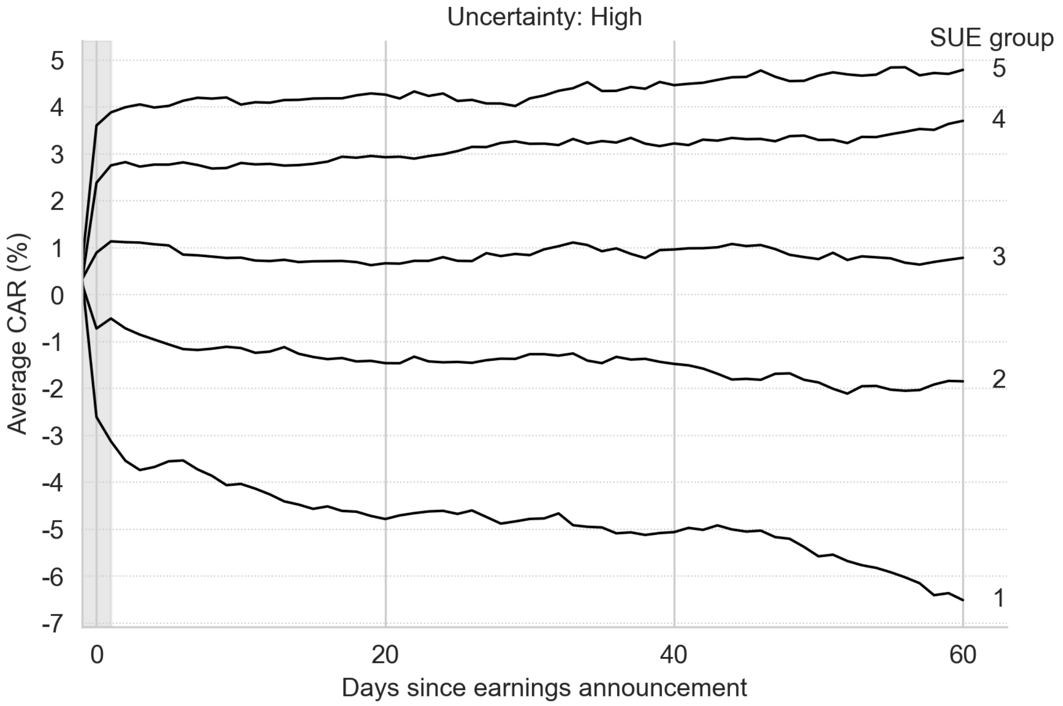
All other steps are the same as described in Section 3.4. For ease of comparison, the CAR(2,60) values are 0.61%, -2.22%, and 2.83% for the High SUE group, Low SUE group, and the PEAD strategy, respectively as can be seen in Table 3. Correspondingly, the BHAR(2,60) values are 0.41%, -2.35%, and 2.75%. From this, we conclude that the magnitude of our estimates using CAR is comparable to those obtained using BHAR, which suggests that a comparison between the two methodologies is, to some extent, warranted. However, we also note that the drift appears slightly more negative when using the BHAR methodology.

Table 10: Buy-And-Aold Abnormal Returns (BHARs) by SUE Quintiles

SUE group	N	BHAR (-1,1)	BHAR (2,20)	BHAR (21,40)	BHAR (41,60)	BHAR (2,60)
High (5)	1929	3.28%***	0.17%	0.27%	0.05%	0.41%
		(0.0018)	(0.002)	(0.002)	(0.0023)	(0.0036)
4	1799	2.35%***	0.02%	-0.00%	0.19%	0.16%
		(0.0015)	(0.0017)	(0.0018)	(0.002)	(0.003)
3	1725	0.72%***	-0.51%***	0.21%	-0.09%	-0.40%
		(0.0014)	(0.0016)	(0.0017)	(0.002)	(0.0031)
2	1899	-1.06%***	-0.57%***	0.18%	-0.23%	-0.65%**
		(0.0015)	(0.0017)	(0.0018)	(0.0021)	(0.0032)
Low (1)	1918	-2.85%***	-1.17%***	-0.50%**	-0.70%**	-2.35%***
		(0.0017)	(0.0023)	(0.0023)	(0.0027)	(0.0043)
PEAD		6.12%***	1.34%***	0.77%**	0.75%**	2.76%***
		(0.0025)	(0.003)	(0.003)	(0.0036)	(0.0056)

The table reports buy-and-hold abnormal returns for portfolios sorted by standardized unexpected earnings (SUE) quintiles across event windows, where day 0 is the earnings announcement date. Abnormal returns are calculated as the difference between the daily stock return and the return of a value-weighted benchmark portfolio matched on firm size and book-to-market ratio. Columns report BHARs for the immediate window BHAR(-1,1), the first month BHAR(2,20), the second month BHAR(21,40), the third month BHAR(41,60), and the full quarter BHAR(2,60). The "PEAD" row shows returns to a long-short strategy that takes a long position in the highest SUE quintile and a short position in the lowest. Standard errors are shown in parentheses. Two-sided p-values are reported. Significance levels are indicated by: ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

E. CAR Figure by Uncertainty



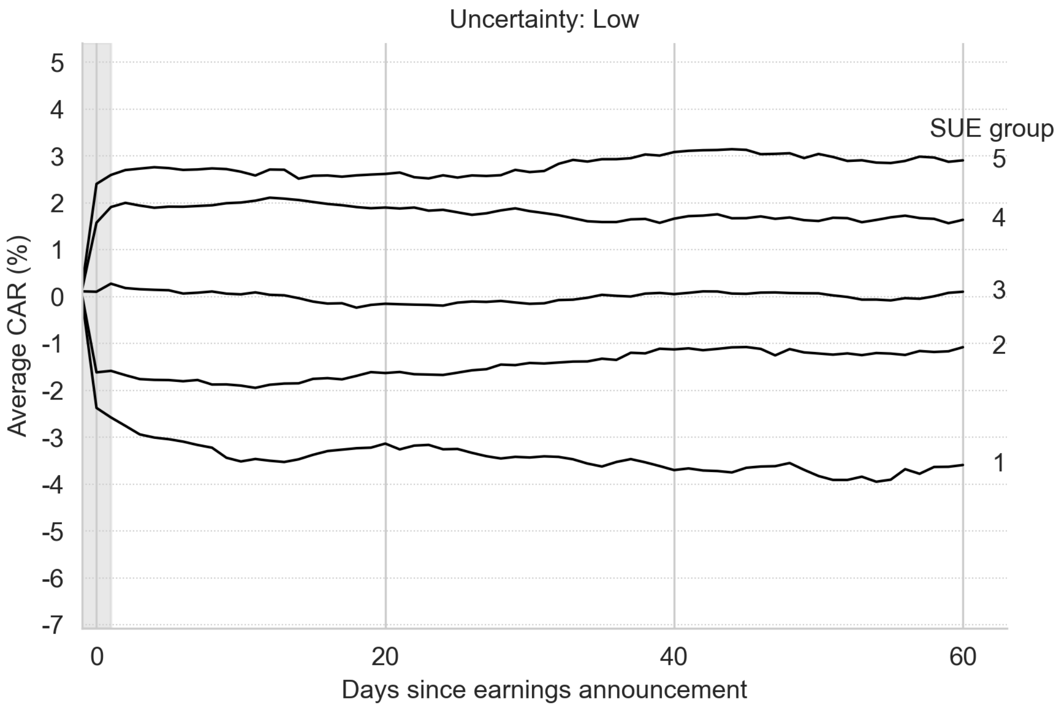


Figure 6: Average cumulative abnormal returns (CAR, %) across standardized unexpected earnings (SUE) quintile portfolios from day t=-1 to t=+60, where t=0 denotes the earnings announcement date, divided between high and low uncertainty firms. The grey area highlights the immediate return window.

F. Additional Robustness Checks

Table 11: Additional Robustness Checks

	FF3 Adjusted Calendar-Time Regression		Wald Test
	$\alpha_{Selective}$	$\alpha_{FullSample}$	$\alpha_{Selective} - \alpha_{FullSample}$
Panel A: Benchmark			
	0.0123***	0.0056**	0.0067***
	(0.0030)	(0.0023)	(0.0025)
Panel B: Varying Number of SUE Groups			
3 Groups	0.0086***	0.0041**	0.0045***
	(0.0023)	(0.0017)	(0.0018)
10 Groups	0.0125***	0.0018	0.0108***
	(0.0047)	(0.0041)	(0.0035)
Panel C: Varying SUE Truncation			
0%	0.0107***	0.0059**	0.0048**
	(0.0033)	(0.0024)	(0.0021)
1%	0.0108***	0.0055**	0.0053**
	(0.0033)	(0.0023)	(0.0023)
5%	0.0127***	0.0064***	0.0063***
	(0.0030)	(0.0019)	(0.0023)
Panel D: Varying Delisting Return Approximations			
+100%	0.0115***	0.0061***	0.0055**
	(0.0032)	(0.0021)	(0.0024)
+/-0%	0.0121***	0.0057***	0.0064***
	(0.0030)	(0.0022)	(0.0024)
-100%	0.0127***	0.0053**	0.0074***
	(0.0031)	(0.0025)	(0.0025)
Panel E: Varying Holding Periods			
6-months	0.0095***	0.0058***	0.0038**
	(0.0026)	(0.0018)	(0.0016)
9-months	0.0075***	0.0050***	0.0026**
	(0.0020)	(0.0014)	(0.0013)
12-months	0.0071***	0.0047***	0.0024**
	(0.0017)	(0.0012)	(0.0011)

Robustness checks for the Fama-French-Carhart 4-factor (FFC4) adjusted calendar-time regression results. The table reports estimated alphas for selective and full-sample PEAD strategies across a range of alternative specifications, along with Wald tests of the alpha differential. Panel A presents the benchmark result. Panels B-E reports results under varying number of SUE groups, the level of SUE truncation, the delisting returns, and the portfolio holding periods. All regressions are estimated using ordinary least squares (OLS) with Newey-West heteroskedasticity- and autocorrelation consistent (HAC) standard errors. Only the estimated alphas and their standard errors are reported for the regressions. The Wald test is based on a seemingly unrelated regression (SUR) framework. P-values are two-sided for the regressions and one-sided for the Wald test. Standard errors are shown in parentheses. Significance levels are indicated by: ***$p < 1\%$, **$p < 5\%$, *$p < 10\%$.

In Table 11 Panel B, we test the robustness of our results to changes in the number of SUE groups, compared to the 5 groups used in the main analysis. When reducing the number of groups to three, our main findings remain robust. However, when increasing the granularity to 10 groups, the abnormal return of the full-sample PEAD strategy is no longer statistically significant. This may reflect a crowding-out effect, where informed investors are already exploiting the drift in the highest SUE decile. Nevertheless, the selective strategy remains significant and continues to outperform the regular strategy. Interestingly, we also find that the abnormal return of the selective strategy increases with the number of SUE groups. A possible explanation is that higher information uncertainty makes the earnings signal harder to interpret, while limits to arbitrage prevent sophisticated investors from fully exploiting the anomaly.

In Panel C, we test the sensitivity of our results to varying levels of SUE truncation relative to the 2.5% threshold used in the main analysis. We find that our main conclusions remain robust when the truncation level is lowered to 0% or 1%, as well when it is increased to 5%. Notably, the abnormal return of the selective strategy rises with higher truncation levels. One possible interpretation is that truncation effectively removes outliers in the SUE distribution, where extreme values may be statistical artifacts and distort the measure.

In Panel D, we examine how the performance of the PEAD strategies varies under different assumptions about the delisting return, compared to the -30% assumption used in the main analysis. Since FinBas does not specify the reason a firm's coverage ends, it is important that the assumed delisting return is robust and appropriate for a range of scenarios.[29] First, we find that our main results are robust to reasonable changes in the assumed delisting return. Second, we observe that assigning a more negative delisting return improves the performance of the selective strategy, whereas assuming a less negative, or even positive, delisting return reduces its performance. One possible explanation is that more negative delisting returns better capture the impact of bankruptcies, which are more likely to involve underperforming firms. Under this assumption, the short leg of the PEAD strategy experiences more negative returns, thereby increasing the overall abnormal return of the long-short strategy.

In Panel E, we extend the holding period beyond the 3 months used in the main analysis. We observe that the abnormal returns of both the full-sample and selective PEAD strategies decline as the holding period increases. This is consistent with our rationale for focusing on the 3-month window, namely that longer horizons are more likely to incorporate confounding influences, such as subsequent earnings announcements. Furthermore, we find that the selective strategy is statistically better than the full-sample strategy at the 5% significance level for all variations in holding periods.

[29]For example, delistings due to bankruptcy versus mergers or acquisitions.

G. AI Disclosure

Generative AI, specifically OpenAI's ChatGPT, has been used as a supportive tool in the process of writing this thesis. The two primary use have been transforming natural language into Python code for the analysis, as well as proof-reading, sentence enhancing, and formatting[30] during the writing process. To a lesser extent, the tools "web search" and "Deep Research" has been used to search for relevant sources. However, in no instance has the output of these tools served as a primary source in the formation of this thesis, but rather acted as an advanced web search.

The primary benefit of using generative AI in this thesis was in increased efficiency. It also helped to bridge gaps in programming knowledge, allowing for easier implementation of statistical tests. Furthermore, it identified minor grammatical and spelling errors that are otherwise easy to overlook. Additionally, the "Deep Research" tool facilitated access to sources that may be difficult to locate through traditional search methods.

However, the use of AI in research also poses several risks. Most notably, AI-generated output can contain hallucinations or inaccurate suggestions. To mitigate this, all sources provided were verified against the original documents. Furthermore, there is a risk that AI may misinterpret the user's intent. For this reason, all Python code generated with AI assistance was carefully reviewed to ensure that it performed the intended operations. Finally, while generative AI can assist in refining language and phrasing, it may unintentionally alter the intended meaning of the text. As such, all AI-generated text suggestions were critically evaluated and only used as inspiration for our writing when deemed appropriate.

The main insight from using AI tools during the thesis process was that they can meaningfully enhance productivity and enable analyses that would otherwise be difficult to complete within the time constraints of the thesis.

[30] Including tables and references.