The granddaddy of underreaction events

POST-EARNINGS ANNOUNCEMENT DRIFT AND INFORMATION NOISINESS ON THE SWEDISH MARKET

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Abstract

This paper aims to answer the question of whether there is an existence of post-earnings announcement drift on the Swedish stock market and to what extent it can be explained by information noisiness. A sample of publicly listed firms on the Swedish stock market from 2002 to 2019 is used and the research design includes four different approaches to estimating earnings surprises which is a crucial step in investigating PEAD. These approaches include a time-series model, a seasonal martingale model, analyst forecasts and event-window return. Further, information noisiness is approximated using stock price synchronicity to try to explain what firms are prominent in the drift. The main findings of the paper provide evidence of PEAD in the market, but the length and magnitude vary depending on the choice if earnings surprise estimate. There is a significant drift in the short run with analyst forecasts as basis, and a significant drift in the long run with seasonal martingale estimates. With the event-window return method, the drift is significant over both short and long holding periods where an annualized abnormal return of 11.4% at a 1% significance level is observed over a 12-month holding period. However, the study does not provide any support for the hypothesis that stock price synchronicity is a driver of PEAD. The main results are robust to alterations in the research design and an implementable investment strategy is presented which exploits the market anomaly, generating excess returns for the potential investor.

Keywords:

Post-earnings announcement drift, market efficiency, earnings surprises, information noisiness, stock price synchronicity

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Happy reading,

Sofia Berlin *Gustav Sandelin*

1. Introduction

The efficient market hypothesis serves as a foundational theory in financial research and states that the market responds immediately and correct to new information which inhibit investors to capture abnormal returns. Numerous empirical studies have been conducted to examine the extent to which financial markets adhere to the principles of efficiency by developing asset pricing models along with investigations of potential anomalies that can be exploited in trading strategies. Critics of the efficient market hypothesis argue that stock prices and returns follow predictable patterns based on past market trends and economic indicators (Lo & MacKinlay, 2002) and that the actions of investors are not always rational and correct. Researchers within the field of behavioral finance agree that observed short-term momentum in stock prices is consistent with human feedback mechanisms, which implies that when people see positive returns on a stock, they will be more inclined to buy (Malkiel, 2003). Researchers further argue for the role of psychology of individual decision making in stock price reactions, where the market's reactions are indeed dramatic overreactions to new information (De Bondt & Thaler, 1985).

> *"If apparent overreaction was the general result in studies of long-term returns, market efficiency would be dead, replaced by the behavioral alternative of De Bondt and Thaler (1985). In fact, apparent underreaction is about as frequent. The granddaddy of underreaction events is the evidence that stock prices seem to respond to earnings for about a year after they are announced." (Fama, 1998)*

Despite that 25 years have passed since Eugene F. Fama referred to the post-earnings announcement drift (PEAD)[1] as 'the granddaddy of underreaction events', the granddaddy is still alive. The underreaction lays in the market's inability to directly and fully incorporate new information from earnings announcements. Rather, the incorporation happens over time, which contradicts the idea of an efficient market (in the semi-strong form) presented by Fama (1970). The first implications of this market behavior were seen in a study by Ball & Brown (1968) where stock price movements in relation to earnings announcements were investigated, but one of the most famous early studies that articulated PEAD as an anomaly is Bernard & Thomas (1989). Their results suggested that an annualized abnormal return of 18% could be earned from buying the decile of firms with the most positive quarterly earnings surprises and simultaneously selling the decile of firms with the most negative quarterly earnings surprises and hold the positions over the following year.

Since Bernard & Thomas (1989), there has been a continuum of papers published where the drift is investigated, and a broad set of explanations and drivers have been suggested and tested. Early explanations related to the market's inability to understand the autocorrelation between quarterly earnings, which surprised the market repeatedly and the anomaly was suggested to be driven by the market reactions around the succeeding earnings announcements. Next to that, a

[1] Throughout the paper, PEAD is also referred to as 'the drift' as well as 'the anomaly'.

common explanation to the drift is related to information uncertainty, for example related to investors' need to properly understand the impact of an earnings announcement which takes time and creates a delayed reaction (Francis et al., 2007). Over time, the test design to investigate the anomaly has been developed and altered. Mainly, this relates to the methodologies used to estimate expected earnings and in turn the earnings surprise, which now constitutes an extensive set. Based on different methodologies, the characteristics of the drift have been shown to change (see for example Ayers et al., 2011; Liu et al., 2003). However, such comparison is to date limited to the largest capital markets. Across markets and throughout time, the tendency of market underreactions to earnings surprises continues to be found and PEAD thus remains a puzzle to academia as it appears to still exist money on the table up for arbitrageurs to grab.

The motive to explore PEAD originates from its relevance for academia, practitioners as well as accounting standard setters. For academia, it is valuable to get a sense of how the anomaly develops over time and across different markets and to get further explanations of the underlying drivers of the drift. Especially since the presence of PEAD challenges the efficient market hypothesis, which is under constant discussion and investigation by researchers. The development of PEAD is furthermore of interest to accounting researchers that seek to understand the true relationship between accounting numbers and stock price reactions. For practitioners, it is valuable to know whether there is systematic mispricing in the market that can be exploited to earn abnormal returns, and what strategies can be undertaken to do so. For accounting standard setters, the development of stock prices after the release of accounting information can provide guidelines of what accounting figures are of most importance to investors, what figures provide the most transparent information, and equally what can potentially lead to mispricing in the market.

Studies on smaller markets does not present as clear drifts as the majority of the empirics from larger markets, such as the US and the UK. This turns smaller markets into an interesting area of research as they are less explored. The Swedish stock market is a well-established market and the sixth largest in Europe (Sveriges Riksbank, 2016). Nonetheless, it is still as small capital market with limited research in the area. Further, the previous evidence on the Swedish market has been contradicting. Setterberg (2011) finds a significant drift over a 12-month period, which is more prolonged than the general drift documented in other markets. In contrast, a more recent unpublished study by Karlsson & Jeganmohan (2020) do not find any drift on the market. Furthermore, there is evidence that argues that the Swedish market has become more efficient over time, as investors interpret information more correctly (Skogsvik & Skogsvik, 2010), which makes it interesting to perform an updated PEAD study on the Swedish market, to see if the evidence of a more efficient market has impacted the presence of the anomaly. Hence, this paper aims to contribute to the current PEAD literature by answering the question:

Is there a post-earnings announcement drift in the Swedish capital market and can it be explained by information noisiness?

The scope of this paper is limited to a sample of 16,122 firm-quarter observations from 634 Swedish non-financial firms listed on the Nasdaq Stockholm Stock Exchange between year 2002 – 2019. We limit our scope to one country to minimize impact from currency, tax and other regulatory effects that potentially could disturb the possibility to implement a PEAD based trading strategy. Further, the scope is limited to firms that are listed on the Nasdaq Stockholm Stock Exchange, thus excluding firms on unregulated open marketplaces, as the study is reliant on accuracy in the financial reports which invokes a common regulation. Financial firms are excluded as their financial statements and reporting practices are substantially different from those of other industries, which give rise to differences in interpretation of accounting numbers. Hence, the sample is more homogeneous and the results more general. The lower date bound is set by access of quarterly earnings announcement dates while the upper date bound is limited by daily dividend-adjusted stock prices. Despite having a relatively long time-horizon, we do not focus on the development of PEAD within the years of our study but the existence of it.

This study's contribution to the current PEAD literature is threefold, with consideration to the market where the study is performed, the methodology applied and the investigation of a new potential driver of the drift in terms of information noisiness. First, the literature has a limited amount of research that have been performed on markets outside the US and the UK, and more importantly, the results outside these markets have been more contradicting. Some smaller capital markets seem to not experience any drift at all, whereas in the Swedish market has contradicting evidence. Second, there is great divergence in the methods used to measure and evaluate PEAD, especially in regard to the estimation process of what expectations the market has on earnings, and thus what is considered to be an earnings surprise. The four main methodologies used in the literature are the seasonal Martingale process, a time-series estimation based on historical earnings development, analyst forecast based, and the event-window return method. To the best of our knowledge, no study has covered and compared all four methodologies simultaneously, which is done in this paper. Further, the Swedish market has been investigated solely through the time-series process and we thus nuance the previous results by introducing several new methodologies. Third, the study adds to the extensive literature that tries to explain the reasons behind the drift in the capital market, by testing if information noise, estimated through stock price synchronicity, is a driver of PEAD.

The remaining parts of this paper is structured as follows. Section 2 presents theoretical background in terms of efficient market theory, the concept of value relevance and accounting information. Section 3 covers the current empirical evidence in the research area of post-earnings announcement drift in terms of characteristics, estimation approaches and drivers. Section 4 presents the data used in the study together with descriptive statistics and section 5 presents the research design applied to investigate our hypotheses. Section 6 presents the main results of the study and section 7 consists of the analysis of the main results as well as an analysis of the research design and robustness tests. Last, section 8 includes the final conclusions and suggests areas of future research.

2. Theoretical Background

2.1. The Efficient Market Hypothesis

The theory of the efficient market hypothesis (EMH) was first introduced in the 1960´s, and states that financial markets are efficient in the sense that prices of securities accurately reflect all available information, and that all new information is incorporated immediately (Fama, 1965). The initial article by Fama attracted a significant number of researchers of economics and finance into the field of efficient markets and has been a subject of intense empirical and theoretical research ever since. Three levels of market efficiency are proposed as a framework to better describe the complexity of the theory of efficient markets and the extent to which stock prices reflect all available information. The three levels are weak form efficiency, semi-strong form efficiency, and strong form efficiency. The weak form of market efficiency is based on the random walk theory which suggests that stock price development follows a random walk, and that current stock prices reflect all the information contained in historical prices. This implies that a potential analysis based historical prices and volumes to predict future prices will not generate excess returns for investors. Thus, historical stock price movements do not contain any information that can be used to predict future stock price movements. The semi-strong form of market efficiency suggests that stock prices reflect all publicly available information. Hence, not only is the information reflected in past prices, but also all publicly available information, such as financial statements, analyst reports and market trends, are incorporated into current prices. This definition implies that analysis which uses publicly available information to predict future stock prices, can never generate excess returns. The strong form of market efficiency suggests that stock prices reflect all information, including public, private or insider information about the underlying assets. This means that despite an investor's potential access to private or insider information about the stock, it is not possible for the investor to consistently attain excess returns (Fama, 1970). Furthermore, as a replay to critics of the definition proposed by Fama, the notion that all available information is interpreted and used fully and correctly was introduced as an assumption that needs to be in place for the definition to hold (Fama, 1976).

Other definitions of market efficiency then the one presented by Fama have been proposed, where heterogenous expectations and information asymmetry have been accounted for, as well as what is meant by the term 'available information'. One definition claims that a market is efficient in regard to a specific amount of information, if prices react as if everyone knew this specific amount of information (Beaver, 1981). This definition is more general as it allows for different expectations and considers the fact that not everyone has the access to the same information, and that investors may interpret information differently. A further definition conditions that a market is efficient in regard to a certain amount of information, as long as it is impossible to create a trading strategy and earn risk adjusted economic profit based on this information, net of all costs (Jensen, 1978). Hence, this definition also considers the presence of transaction costs in the market.

The semi-strong form efficiency presented by Fama is often used as the definition of an efficient market in accounting research. Thus, the semi-strong form efficiency serves as the definition of an efficient market in this study. In the next section, the concept of value relevance, accounting information and the relationship to stock prices are discussed further.

2.2. Value relevance and the role of earnings

When new accounting information is released, it is crucial to understand whether the information has value relevance. The concept of value relevance can be defined as the information's ability to predict variables in stock price valuation models, or if the information itself can be used in such valuation models (Francis & Schipper, 1999). A large number of empirical studies have stated that value relevance can be confirmed by the statistical association between accounting information and observed stock prices (Francis & Schipper, 1999; Holthausen & Watts, 2001). Figure 1. Presents a visualization of the relationship of accounting information and motivated values of stock prices.

Accounting information → Exogenous variables in valuation model → Motivated value of stock according to valuation model

Figure 1. Relationship between accounting information and the motivated value of stocks

Consider for instance the dividend-discount model, which determines the motivated value of a stock as the present value of all future dividends, presented in equation 1a (Berk & DeMarzo, 2017). New accounting information does not necessarily state what the future dividends will be, but for example a change in the quarterly earnings development may contain information that changes the expectations of future dividends. Through such implicit impact on the motivated value, the accounting information has value relevance.

$$P_0 = \sum_{t=1}^{\infty} \frac{E_0[Div_t]}{\prod_{\tau=1}^{t}(1+r)} \tag{1a}$$

where:
P_0 = Price at point 0
$E_0[Div_t]$ = Expected dividend at time t
r = the discount rate

Further, consider equation 1b where the dividend is divided into earnings and pay-out ratio. In that case, the accounting metric earnings itself presents an exogenous variable in the valuation model. Under the assumption that a change in earnings does not change the firm's payout ratio, the earnings figure has a clear linkage to the motivated stock price.

$$P_0 = \sum_{t=1}^{\infty} \frac{E_0[Earnings_t] * E_0[pr_t]}{\prod_{\tau=1}^{t}(1+r)} \tag{1b}$$

where:
$Earnings_t =$ the expected net earnings at time t
$pr_t =$ the expected pay-out ratio at time t

Although new accounting information may be value relevant, whether an effect on a stock's price (or trading volume) occur is dependent on an investor's perception of whether the information has relevance to the motivated value and further acts on it. In this paper, we assume that quarterly earnings announcements contain value relevant information and thus that surprises in earnings imply that the information is also new, which would motivate a market reaction. With such assumption, whether the market is efficient is dependent on the investors' perception and reaction to the announcement, where an immediate and correct reaction implies an efficient market.

2.3. Accounting information and stock market reactions

Extensive research has been conducted to investigate if the EMH holds in relation to publication of accounting information, given the findings that accounting information have value relevance. (Ou & Penman, 1989) study if it is possible to obtain an abnormal return by setting up a trading strategy based on earnings forecasts and other key accounting figures and find that their strategy generates an abnormal return for a period of up to 2 years. Whether this study is evidence of an inefficient market or not have been heavily debated, where others argue that the risk adjustment was not properly done and with other adjustments for size there is no abnormal return and thus the EMH still holds (Greig, 1992). If the stock market's reaction to specific accounting choices, such as asset write-offs, is immediate and correct or whether there is a drift following the announcement and find that following the bad news of a write-off there is a significant negative drift in stock prices (Bartov et al., 1998). The results might imply that there is an initial underreaction from investors because they do not understand this new accounting information fully, which speaks in favor of the market not being semi-strong form efficient. Another studied relationship between accounting choices and stock market reactions is the case of cosmetic accounting, where the EMH implies that even if a firm is accused of engaging in cosmetic accounting it will not impact its stock price, as the accusation does not consist of new information. In contradiction, Foster (1979) find that the market is misled by these choices and that the market reacts to these accusations, which indicates that the market fails to fully understand the accounting numbers presented by firms. Furthermore, earnings figures have been subject to substantial amount of research, both in terms of the markets ability to foresee future earnings as well as the market's interpretation and reaction to announced earnings. The research field of PEAD is an evaluation of whether the EMH holds, as PEAD is an observed anomaly in market movements after the publication of new information. If the semi-strong form efficiency holds, the anomaly cannot exist as there should not be any abnormal return after an earnings announcement, except at the immediate time of the announcement if the information is new and value relevant, when a complete adjustment to the new information is incorporated.

3. Empirical evidence

3.1. The post-earnings announcement drift characteristics

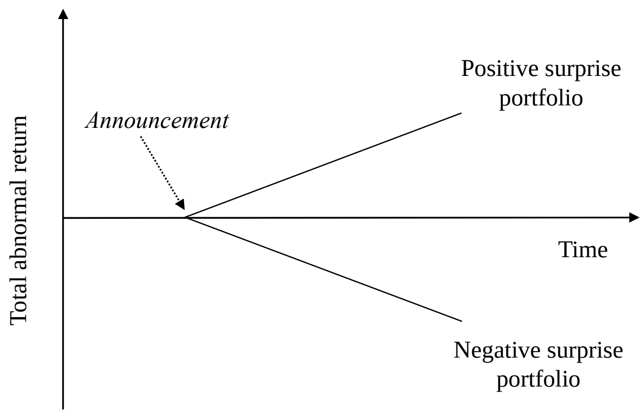

Figure 2. Stylized illustration of PEAD

The post-earnings announcement drift is an anomaly in the stock market that refers to the tendency of stocks to continue to drift in the direction of their initial price reaction following a news announcement (see figure 2 for illustration). These movements go against the semi-strong form of EMH, which implies that the new information should be fully incorporated in the stock price immediately (Fama, 1970). This was first seen by Ball & Brown (1968), when the conducted a study under the assumption that the EMH holds, and they documented stock price reactions surrounding earnings announcement. The focus of the study was to analyze stock price reactions prior to the announcement, however, in their result they also document a drift following the announcement. The systematic drift in stock prices following quarterly announcements was further documented by Foster et al. (1984). Subsequently, Bernard and Thomas (1989) investigate stock price reactions following earnings surprises on the US stock market for the time period of 1974 to 1986. They create 10 portfolios with 5 portfolios of positive earnings surprises and 5 portfolios of negative earnings surprises and create an investment strategy that suggest going long in the most positive surprise portfolio and going short in the most negative earnings surprise portfolio. The result show that an investor pursuing this strategy can obtain an annualized abnormal return of 18% over a 12-month (240-trading days) holding period (Bernard & Thomas, 1989). Hence, the stock price reactions to new information in terms of earnings surprises, is not immediate, but rather keep drifting over a longer period of time which implies a further contradiction to the EMH.

Below follows table 1 with a summary of some of the foremost articles in the extensive PEAD literature since the first discovery. *Market* refers to what geographical market the study is researching. *Time period* is the period that data has been collected from and with what frequency. *Expected earnings* refers to what type of approach have been applied when estimating excepted earnings to obtain the earnings surprise. *Event window* refers to the immediate time around the announcement where the new information is assumed to be received by the market. *Holding period* refers to the time period that the position has been held when measuring abnormal returns. *Risk adjustment* refers to the method used to determine what the excepted return is and thus what is the abnormal return. *Abnormal return* refers to what metric have been used to estimate the total abnormal return that can be obtained. *Results* refer to the total anormal return an investor can achieve by taking both the LONG and SHORT position (if specified in paper). *PEAD* refers to whether there is a significant PEAD detected in the study. *Comments* is a short summary of interesting conclusions from the paper.

Table 1. Overview of empirical PEAD studies

Authors	*Market*	*Time period*	*Expected earnings*	*Event window*	*Holding period*	*Risk adjustment*	*Abnormal return*	*Results*	*PEAD*	*Comments*
Bernard & Thomas (1989)	US	1974-1986 (quarterly)	Time-series	+ 1 day	12 months	CAPM and size-adjusted	CAR, BHAR, monthly alpha	18% annualized return	Yes	First study with evidence of PEAD
Van Huffel et al. (1996)	Belgium	1990-1993 (semi-annually)	Time-series	± 1 day	90 days	CAPM and size-adjusted	CAR	No drift	No	No evidence of PEAD, drift for large firms argued to be due to weak prediction model
Liu et al. (2003)	UK	1988-1998 (semi-annually)	Time-series, analyst forecasts and event-window return	n.a. (calender method)	3,6,9,12 months	Three-factor model	BHAR, monthly alpha	10.8% yearly return	Yes	Event-window return presents highest significance for PEAD
Livnat & Mendenhall (2006)	US	1987-2003 (quarterly)	Seasonal martingale and analyst forecasts	+ 1 day	3 months	Size and M/B-adjusted	CAR	5.2% quarterly return	Yes	PEAD is larger when estimating expected earnings with
Francis et al. (2007)	US	1982-2001 (quarterly)	Analyst forecasts	n.a. (calender method)	6 months	Three-factor or four-factor model	Monthly alpha	-	Yes	Firms characterized by high information uncertainty have higher PEAD
Booth et al. (2011)	Finland	1995-2003 (quarterly)	Event-window return	± 1 day	30 days	Set of control variables	CAR	-	Yes	The drift is significant for negative surprises; investors only underreact to bad news
Setterberg (2011)	Sweden	1990-2005 (quarterly)	Time-series	n.a. (calender method)	6 and 12 months	CAPM and three-factor model	BHAR, monthly alpha	11.4% annualized return	Yes	The drift appears more prolonged than other markets, only significant for 12 months
Ayers et al. (2011)	US	1993-2005 (quarterly)	Seasonal martingale and analyst forecasts	± 5 days	60 days	Three-factor model	CAR	-	Yes	More prominent, shorter drift with analyst forecasts, explained by investor sophistication
Milian (2015)	US	1996-2010 (quarterly)	Analyst forecasts and event-window return	+1 day	30 and 60 days	Size and M/B-adjusted	CAR	-	Yes	PEAD is now concentrated over shorter period due to unsophisticated investors
Wang et al. (2017)	US	1996-2014 (quarterly)	Analyst forecasts	+ 2 days	60 days	CAPM	BHAR	-	Yes	Investor attention leads to more timely responses to announcements
Dargenidou et al. (2018)	UK	1995-2013 (semi-annually)	Analyst forecasts	+10 days	6 months	Set of control variables	BHAR	3.4% semi-annual return	Yes	Contrarian insider trading eliminates the drift, confirmatory insider trading amplifies the drift
Clement et al. (2019)	US	1984-2010 (quarterly)	Seasonal martingale and analyst forecasts	+ 2 days	3 months	Size and B/M-adjusted	CAR	6.1% and 7.0% quarterly return	Yes	Drift based on analyst forecast is greater than time-series
Zhang & Gregoriou (2020)	UK	2000-2015 (quarterly)	Seasonal martingale	± 1 day	60 days	Size-adjusted	CAR	-	Yes	PEAD is related to the information asymmetry of zero-leverage firms
Li et al. (2020)	US	1990-2013 (quarterly)	Analyst forecast	+ 2 days	3 months	Three-factor model	CAR	-	Yes	Delayed disclosure of financial information is a driver of PEAD

3.1.1. Global spread and variations

As seen in table 1, research on PEAD has been conducted across different markets but the field of studies is mainly focused on the US and UK market. Nevertheless, PEAD is a global phenomenon that is found both in highly developed financial markets as well as less developed emerging markets (Griffin et al., 2010). Several country-level studies have documented the existence of PEAD across the world, which for example includes the financial markets of the Canada (Chudek et al., 2011), UK (Liu et al., 2003), Spain (Forner & Sanabria, 2010), China (Truong, 2011), and India (Sen, 2009). Nonetheless, there are exceptions where researchers have not been adle to identify the drift in specific markets. Smaller financial markets such as Belgium (Ariff et al., 1997; van Huffel et al., 1996) and Singapore (Ariff et al., 1997) do not seem to be characterized with a persistence drift following earnings surprises. The drift is solely identified for the top largest firms in Belgium. The suggested explanation is that PEAD is of a stronger magnitude and more persistence in larger financial markets and that smaller financial markets in general are given less attention and analysis by investors which weakens the overall effect from earnings announcements on stock prices (van Huffel et al., 1996). In Finland, there appears to be only a negative drift, and the results imply that the presence of foreign investors is of importance as their information processing of earnings announcements is more efficient than domestic investors and, that the drift is a result of this (Booth et al., 2011). The financial market of Sweden is investigated in one published article, where PEAD is identified on a sample based on data between 1990-2005. The conclusion suggests that by taking a long position in the portfolio of companies with the highest earnings surprise and selling the portfolio with the lowest earnings surprise, an investor can earn an annualized abnormal return of 11.4%. In addition, she finds that the drift appears to be more prolonged in this market compared to other studied markets (Setterberg, 2011). In contrast to this, an observation was made more recently where PEAD appeared to have disappeared on the Swedish market (Karlsson & Jeganmohan, 2020). The concept of PEAD was not the primary research topic of the paper, nonetheless the results contribute to the puzzle of whether PEAD does exists in smaller capital markets and if it does still exist on the Swedish market.

The long stream of literature has resulted a lot of documentation of how PEAD also varies over time. Since the first documentation of PEAD there has been enormous change in stock trading technologies and the regime of more liquidity in financial markets have led to decrease in the economic and statistical significance of PEAD and other stock market anomalies (Chordia et al., 2014). This attenuation of the drift is also supported by a more recent study which suggests that after considering accounting transaction costs, PEAD is only marginally significant (Richardson et al., 2010). The diminishment of PEAD is further argued to be driven by the spread of knowledge about PEAD as it attracts arbitrageurs to profit from the anomaly which shortens the drift in time. The spread of knowledge also gathers unsophisticated investors that overreact in the short run, which creates a reversal of the drift (Milian, 2015). In addition, improved and more easy access to information about firms, seem to reduce the drift during the months of trading after the announcement (Fricke et al., 2014). Nevertheless, the majority of the continuum of studies in the research area do find evidence of PEAD in their attempt to refine and challenge previous methodologies or explain the drivers of the drift, which contributes to the perpetual curiosity surrounding the field.

3.2. The estimation process

Over the last decades, different methodologies have been used to investigate the PEAD phenomenon, mainly with regards to the quantification of the earnings surprise (or the expected earnings figure) and the approach to estimate the riskiness of the portfolio to observe the potential abnormal return. This subsection presents the different methodologies used to investigate PEAD and the implications of each of them.

3.2.1. Earnings expectations and surprises

An earnings surprise is defined as the difference of the actual earnings that a firm report and the earnings expected by the market up until the announcement.

$$Earnings\ surprise_t = Earnings_t - E_0[Earnings_t] \tag{2}$$

To determine the surprise, it is essential to start to assess what earnings the market is expecting. An assessment that is not as straightforward as one would initially think. Hence, the literature of earnings surprises and PEAD provide a broad variety of approaches (see table 1) and new adaptations are constantly developed by researchers. The characteristic of the drift is further shown to differ depending on the approach used (see for example Ayers et al., 2011; Liu et al., 2003). The estimation of earnings expectations can broadly be divided into three groups, a historical figures approach, an analyst forecast approach, and a return-based approach. Each group will now be discussed in further detail.

Historical figures approach

To estimate the expected earnings based on historical figures, the most simplistic methodology is the seasonal Martingale approach (see for example Ayers et al., 2011; Clement et al., 2019; Livnat & Mendenhall, 2006). In this methodology, the earnings from the same quarter last year serves as the base for expected earnings for the current quarter, which makes all changes in earnings defined as a surprise. The simplicity and straightforwardness of the method makes it convenient to use. However, the simplicity can equally be considered a drawback of the method since it fails to incorporate any firm specific information and macroeconomic changes that have occurred in the surpassed year. Nevertheless, it is likewise suggested that more sophisticated methods do not necessarily affect the result considerably in event studies (MacKinlay, 1997). An early and more sophisticated methodology that builds on historical figures, but includes the trend of the earnings development, is the time-series approach (see for example Bernard & Thomas, 1989; Setterberg, 2011). The expected earnings figure is estimated through a time-series analysis on a rolling basis with regards to previously reported development of quarterly earnings. The estimation can be based on a pre-set fixed number of quarters or based on all quarterly data available within a maximum and minimum number of quarters, ranging between 9 and 24 quarters (Bernard & Thomas, 1989; Liu et al., 2003; Setterberg, 2011). The main argument in favor of the time-series approach is that is captures trends in profitability which is considered reasonable as it exists an autocorrelation between quarters (Bernard & Thomas, 1990). However, the method has the same flaw as the seasonal martingale approach, where adding more historical figures does not necessarily add predictionary power to the proximate future. To conclude, the main arguments in favor for the historical figures approach are the inclusiveness and neutrality of the method, as all stocks with sufficient historical earnings data can be included and it provides an unbiased estimate of expected earnings. The main drawback is the lack of forward-looking attribute, as the estimate is based solely on past performance and historical data.

Analyst forecast approach

In contrast to the focus on historical figures, another approach to estimate expected earnings is the forecasts presented by analysts and investors. The method is considered appropriate as it provides a more forward-looking approach than the historical figures approaches and is more closely related to reality, as investors tend to look at analyst estimates rather than statistical methods on historical performance (Brown et al., 1987). It is further argued to present a more accurate estimate, as it is based on multiple independent analysts forecasts that consider current market trends and presented forecasts can have a significant direct impact on stock prices. The amplitude of PEAD when utilizing analyst forecasts is found to be larger than with historical figure approaches (Doyle et al., 2006; Livnat & Mendenhall, 2006), but additionally that the realization of the drift is faster (Clement et al., 2019). This has been rationalized by the idea that more sophisticated investors tend to rely more on analyst forecasts and that they react more rapidly to shocks (Ayers et al., 2011). Nevertheless, the method is flawed by the scarcer quantity of data needed to use it, as most companies with a great amount of analyst following are large corporations, which creates an inevitable selection bias in the sample (Livnat & Mendenhall, 2006). Yet, the amount of information analysts have access to has dramatically increased, which speaks in favor of the approach as their forecasts might represent more accurate expectations. However, it is also argued that analyst forecasts are biased and that analysts fail to understand and incorporate all public firm information, which creates flaws their forecasts of future expected earnings (Abarbanell & Bushee, 1998; Lee, 2012).

Return-based approach

A third approach to quantify the earnings surprise is the application of abnormal event-window returns (see table 1). The rationale behind this method is that earnings announcements come with significantly more information than net earnings, both in terms of other financial information, such as revenue development, and non-financial information which also affect the assumed development for the company going forward. By observing the initial stock price reaction through an abnormal return metric, this method aims to catch all information included in and around the earnings announcement and thus give a more comprehensive view on the surprise (Gerard, 2012; Kishore et al., 2008). One advantage of this approach is that it is simple measure which is straightforward for investors to calculate with stock price data only. When using the return-based approach, PEAD is found to be larger which is explained by the other two estimation processes being subsumed by the comprehensive return-based approach (Liu et al., 2003). The drawbacks of the method are the uncertainty related to what one should expect given the riskiness of each asset and the noise from observing stock price movements over such a short period. Further, it adds no explanatory value to the drivers of a surprise.

3.2.2. Expected return

One of the eternal questions within the finance literature is how to estimate the risk of an asset, to be able to properly discount future expected cash-flows. Excess return is not abnormal if it stems from a higher risk, and one must thus be careful to say that abnormal return can be earned from a trading strategy as it may just be an effect of excess risk taken on. In turn, it is important to take risk into account during investigation of PEAD to be able to say anything about the existence of an abnormal return.[2]

The most established method used to estimate risk of an asset is the capital asset pricing model (CAPM), where the return of the asset is regressed on the return for the market to find the covariance between the two (Sharpe, 1964). The rationale behind the model is that all firm-specific risk can be diversified away by owning the market portfolio and the risk of an asset is thus just its correlation with the market's. Thus, the estimated expected return for an asset, is calculated as follows:

$$E_0\left[R_{i,t}\right] = R_{f,t} + \beta_i\left(R_{m,t} - R_{f,t}\right) \tag{3}$$

where:
$E_0\left[R_{i,t}\right]$ = expected return for firm i at time t
$R_{f,t}$ = the risk-free rate at time t
β_i = the firm-specific risk of firm i, calculated as the covariance between the firm i's return and the market return scaled by the variances
$R_{m,t}$ = the market return at time t

After the introduction of the CAPM, the model has been criticized for not fully capture the riskiness of an asset, but rather 70 percent (Fama & French, 1993). This can be explained as an effect of the estimation process which leads to an overestimation of high-beta assets and an underestimation of low-beta assets (Fama & French, 2004). However, until this day CAPM is

[2] Throughout this paper, the following definition of return for an asset over one period is used:

$$R_t = \frac{P_t + Div_t}{P_{t-1}} - 1$$

where:
R_t = return at time t, P_t = the price at time t, Div_t = dividend paid out in time t

one of very few theoretically founded models. In early studies, CAPM was the one used by most PEAD studies (see table 1). To increase the amount of risk explained, a continuum of literature investigated characteristics of firms with higher expected returns and thus risk. Such examples of these found that firms with low market capitalization had higher returns than firms with high market capitalization as well as high book-to-market (B/M) ratio overperformed those with low, which laid ground for the Fama-French three-factor model (Fama & French, 1993), which is specified as follows:

$$E_0[R_{i,t}] = R_{ft} + \beta_i^1 * (R_{mt} - R_{ft}) + \beta_i^2 * SMB_t + \beta_i^3 * HML_t \tag{4}$$

where:
$E_0[R_{i,t}]$ = expected return for firm i at time t
R_{ft} = risk-free rate at time *t*
β_i^1 = coefficient to link market excess return and return for firm *i*
R_{mt} = market return at time *t*
β_i^2 = coefficient to link *SMB* risk premium to return for firm *i*
SMB_t = estimated risk premium for small stocks over big at time *t*
β_i^3 = coefficient to link *HML* risk premium to return for firm *i*
HML_t = estimated risk premium for high B/M over low B/M at time *t*

To calculate the size risk factor (*SMB*), Fama & French sorted all stocks in their sample based on their market capitalization. They then formed two portfolios: one portfolio containing the stocks with the smallest market capitalizations (the "small" portfolio), and another portfolio containing the stocks with the largest market capitalizations (the "big" portfolio). Similarly, to estimate the value factor (*HML*) all stocks in their sample were sorted based on B/M. They then formed three portfolios: one portfolio containing the stocks with the highest 30% of B/M ratios (the "value" portfolio), one containing the stocks with the lowest 30% of B/M ratios (the "growth" portfolio) and one neutral with the middle 40%. The portfolios are then combined to create six portfolios based on respective categorization, as described in table 2.

Table 2. The Fama-French factors estimation process

Size factor	Value factor	Portfolio
Small – 50%	Value (High) – 30%	1
	Neutral (Medium) – 40%	2
	Growth (Low) – 30%	3
Big – 50%	Value (High) – 30%	4
	Neutral (Medium) – 40%	5
	Growth (Low) – 30%	6

Note: SMB and HML are constructed by first dividing the total market into six portfolios based on size and value factor. The size factor is represented by the market capitalization of the firm, and the value factor is based on the B/M ratio of the firm. The SMB factor constitutes the difference between the mean return of the small portfolios and the mean return of the big portfolios. The HML factor constitutes the difference between the mean return of value portfolios and growth portfolios.

The SMB factor is calculated as the difference between the mean return of small portfolios (1-3) and big portfolios (4-6). Similarly, the HML factor is calculated as the difference between the mean return of value portfolios (1 and 4) and growth portfolios (3 and 6).

$$SMB = \frac{R_1 + R_2 + R_3}{3} - \frac{R_4 + R_5 + R_6}{3} \tag{5}$$

$$HML = \frac{R_1 + R_4}{2} - \frac{R_3 + R_6}{2} \tag{6}$$

where:
$R_x =$ return of portfolio x, based on definition of value/growth, small/big stocks in table 3
$SMB =$ estimated risk premium for small stocks over big stocks
$HML =$ estimated risk premium for value over growth stocks

In the original estimation, monthly returns on the US market were used to estimate the premiums. Over time, premiums have been estimated daily, weekly and yearly across markets. The model has been questioned as the premiums does not hold in every period and rather should be interpreted as persistent market anomalies (Haugen, 2002). However, as seen in table 1, an absolute majority of the papers on PEAD published after the introduction of the model use the Fama-French three-factor model or control for the same characteristics with another set of variables. In Francis et al. (2007), which is the paper using more than three, the fourth factor is an accounting quality factor (introduced by Francis et al., 2005) which has not been established as a common risk-factor.

3.2.3. Abnormal return

When the expectation of the return is set, one can identify the abnormal return as the excess return of an asset over its expectations, as follows:

$$AR_{i,t} = R_{i,t} - E_0[R_{i,t}] \tag{7}$$

where:
$AR_{i,t} =$ abnormal return of firm i at time t
$R_{i,t} =$ return of firm i at time t
$E_0[R_{i,t}] =$ expected return of firm i at time t

To estimate the abnormal return over a period, three different methods is mainly used in the literature, the buy-and-hold abnormal return (BHAR), the cumulative abnormal return (CAR) or through a calculation of alpha from excess return. The foundation of BHAR is to take a position at the beginning of the post-event period and hold this until the post-event period ends to then calculate the difference in net return and expected return as follows:

$$BHAR_{i,T} = \prod_{t=1}^{T}\left(1 + R_{i,t}\right) - \prod_{t=1}^{T}\left(1 + E_0\left[R_{i,t}\right]\right) \tag{8}$$

where:
$BHAR_{i,T}$ = the buy-and-hold abnormal return for firm *i* over period T
T = holding period
$R_{i,t}$ = return of security i at time *t*
$E_0\left[R_{i,t}\right]$ = expected return of firm i at time t

BHAR corresponds to a treatment of the post-event period as one period rather than an accumulation of several, which makes it indifferent to data frequency. In the literature, most of the studies use market return as the expectation level when BHAR is calculated. This is to get a first indication of whether a drift occurs, and in a later stage regress the BHAR at the risk factors. The main argument used in favor for BHAR is that the approach is implementable and corresponds to how positions are generally taken in practice (Barber & Lyon, 1997), while a recurring argument against it is that the absence of rebalancing amplifies the observed abnormal return from compounding (Fama, 1998). In contrast, CAR sums the abnormal returns over the specified period through the following equation:

$$CAR_{i,T} = \sum_{t=1}^{T} AR_{i,t} \tag{9}$$

where:
$CAR_{i,T}$ = the cumulative abnormal return for firm *i* over period T
T = holding period
$AR_{i,t}$ = abnormal return of firm *i* at time *t*, see equation 7

The application of CAR solves the problem with compounding abnormal returns but comes at the cost of being difficult to implement in practice as the portfolio needs to be rebalanced daily (Barber & Lyon, 1997; Fama, 1998). The method is however the most used in the literature (as seen in table 1) as it is viewed as the more theoretically correct.

The third methodology to calculate abnormal returns seen in the literature is through the estimation of alpha from a regression of excess return for a firm or portfolio on the explanatory factors included. In a general setting, the regression can be written as:

$$R_{x,t} - R_{f,t} = \alpha + \sum_{i=1}^{n} \beta_i * factor_i \tag{10}$$

where:
$R_{x,t}$ = the return for asset x (portfolio or firm) at time t
$R_{f,t}$ = the risk-free rate at time t
α = constant abnormal return estimated unexplained by the factors
β_i = coefficient to link explanatory factor i to excess return for asset x
$factor_i$ = estimated premium for specific risk i, such as market risk premium

A famous implementation of this methodology is referred to as *Jensen's Alpha*, where the factor included is the market risk premium and this measure thus relates closely to CAPM. In the PEAD literature, the most common implementation is based on monthly returns for an earnings surprise portfolio (hence referred to as monthly alpha in table 1). From the regressions, one receives an average abnormal return per month over the months included. In this setting, the compounding effect seen in BHAR is limited to one month while rebalances is assumed once per month which make it partly solve the flaws of the forementioned methodologies. However, as one solely receives a monthly average abnormal return metric, it is less convenient to follow the development over different periods which is usually of interest in the field. Several studies combine alpha with either CAR or BHAR, where a simplified version of CAR or BHAR (e.g., market-based) often is used to get a first sense of the drift while the implementation of alpha is used to assess the significance of the PEAD (see for example Bernard & Thomas, 1989; Liu et al., 2003; Setterberg, 2011).

Event window and holding period

To investigate whether a drift occurs, an event study methodology is used in the PEAD literature. The event window is defined as the announcement date and a number of days prior and after, the longest window used have been 10 days after announcement to ensure that all investors have had the time to incorporate the new information (see table 1). After the event window, the drift is investigated over a holding period. The sample is divided into portfolios based on the amplitude of the earnings surprises observed. The difference in abnormal return of the portfolio with the most positive surprise and the portfolio with the most negative surprise is compared to determine the excess return from a hedge portfolio of buying (selling) the portfolio of most positive (negative) earnings surprise over the period after announcement. The holding period where the drift is investigated in early studies consist of several quarters and extends to up to a year but is generally shorter in more recent studies, ranging from just 30 days up to 6 months. This is motivated by the finding that the drift is strongest during the first days following the announcement and the days surrounding the next announcement. The length of the holding period is also motivated with the characteristics of the market investigated, e.g., in the UK is semi-annual earnings announcement are more common than quarterly which motivates a longer holding period (Dargenidou et al., 2018). In addition, more recent findings argue the drift is becoming more concentrated to a shorter period after the announcement (Milian, 2015). Nonetheless, Setterberg (2011) who study the Swedish stock market only find a significant drift for a longer holding period of 12 months, which is rare in comparison the main stream of literature in other markets.

Event-time verses calendar-time regressions

The method that defines an initial event window and a following holding period based on announcement dates is referred to as the event-time method, alternatively a number of studies apply the calendar-time method (see table 1). With the calendar-time method, the firm-specific quarterly announcement date is disregarded and instead, the long and short positions are taken on the first calendar day of the following quarter or month after the announcements, and the drift is measured starting from this day. The calendar-time method is a less theoretical, more practical strategy as all portfolio investments are executed simultaneously and with all necessary knowledge at hand at the time when the investment decision is taken. Thus, the calendar-time method represents an investment strategy that can be implemented by investors in practice. However, this method fails to incorporate immediate reactions to new information as a great number of trading days after the announcement are not examined, whereas the event-time method allows for evaluation of the full period, including the immediate reactions. Hence, the event-time method presents a more theoretically correct method.

3.3. Drivers of the post-earnings announcement drift

Since its origin, researchers have tried to understand the underlying source and drivers of the drift. An early explanation stems from the autocorrelation of earnings between quarters, i.e., a positive (negative) earnings surprise tends to be followed by yet another positive (negative) surprise. The results suggests that investors fail to fully understand the implications of current quarterly earnings surprises for future quarterly earnings (Bernard & Thomas, 1990), which causes the drift. In table 1, several alternative explanations for the drift are presented. Investor attention is one commonly identified driver of the drift, where firms with higher attention experience a smaller drift. Option trading prior to announcements, media coverage, number of announcements on the same day and what day of the week the earnings are disclosed are examples of proxies for investor attention (Wang et al., 2018). The overall investor sophistication in the specific market is another factor that is found to impact the magnitude of the drift, where unsophisticated investors fail to incorporate information in their estimates and thus do not react as correctly as larger more sophisticated investors do (Ayers et al., 2011; Booth et al., 2011). Further, investors fail to integrate the systematic effect accounting conservatism has on reported quarterly earnings, and thus cannot make accurate quarterly forecasts through time-series analysis (Narayanamoorthy, 2006). From the firm perspective, poor financial disclosure readability and delayed quarterly reporting contribute to the drift, as investors cannot process and act on the earnings information correctly and in a timely matter (Lee, 2012; Li et al., 2020). Alternative firm-specific information flows, such as insider trading, is also identified as a driver of PEAD, which is rationalized as trades by insiders contains an important signaling value to the market of whether the new earnings level is persistent or transitory (Dargenidou et al., 2018). Other examples of drivers to the anomaly identified in the literature are failure to consider the implications of inflation (Chordia & Shivakumar, 2005) and the liquidity risk of the firm and other transaction costs (Zhang & Gregoriou, 2020). A common denominator for several of the drivers is the relation to uncertainty stemming from information noise in the disclosure and the market, which is the focus in this paper. In the next subsection, empirical findings related specifically to information uncertainty and noisiness are discussed.

3.3.1. Information Noisiness

For the financial market to be able to react correctly to new information, it is crucial that there is clarity concerning what the implications of the new information are. In the case of earnings announcements that include an earnings surprise, the question of to what extent a new level of earnings is believed to be persistent poses the greatest factor of information uncertainty. Francis et al. (2007) predict that information uncertainty, defined as the extent to which reported earnings maps into operational cash flow, is predicted to be a driver of the drift. Consistent to this prediction, they find that stocks with the greatest earnings surprises additionally have a higher level of information uncertainty, and that reactions following the announcements of earnings are more muted and thus drive the PEAD (Francis et al., 2007). Whether the new earnings figure is an indication of persistent change or just a contingency is further found to be dependent on whether the surprise is driven by a surprise in revenue or expenses, being more persistent if driven by a revenue surprise (Ertimur et al., 2003). Furthermore, earnings announcements include extensive information, in terms of both financial and non-financial information, all of which needs to be considered when evaluating the value and price of a stock. How each separate investor interprets the new information is affected by cognitive biases and their information processing, where investors tend to underestimate reliable earnings reports and focus more on the extremes of available information (Liang, 2003), which the psychological literature argues to be related to the level of noise in the information (Chen & Doukas, 2020). The level of information noisiness can be quantified with a variety of measures, where common proxies used in literature to explain stock price anomalies consist of bid-ask spread, trading volume and analyst coverage and dispersion, which in different ways exploit the differentiated views among important market attendants (Chen & Doukas, 2020). Stock price synchronicity is a measure that captures firm-specific information noisiness through the individual firms' stock price movements which is not explained by the movement of its industry and/or the market (Durnev et al., 2003). The advantage of using such measure is that the proxy aims to capture all information noisiness, as it is based on the cumulative market reaction (Roll, 1988) in contrast to the other forementioned measures which present more specific elements of information noisiness.

Stock price synchronicity

Stock price synchronicity is defined as the extent to what market and industry returns explain the returns of a security. This is quantified through a regression of the return for the security on the market and industry return over a period, where stock price synchronicity is the R^2 from the regression (Roll, 1988). Firms with high stock price synchronicity thus has less firm-specific information which capture both lack of information and high information uncertainty (Chen & Doukas, 2020). Stock price synchronicity is found negatively correlated with accounting quality, both on a firm level (Dong et al., 2016; Hutton et al., 2009) and collectively where stocks on less regulated markets experience higher synchronicity in general (Morck et al., 2000). As mentioned previously, poor financial disclosure quality has also been documented to be a driver of PEAD (Lee, 2012). Further, it is found to be valuable for management as the information that can be extracted from the movement enables better capital budgeting decisions. Thus, firms with high stock price informativeness is more economically efficient (Durnev et al., 2004). Further, more recent studies find that the momentum anomaly can partially be explained by stock price synchronicity where firms with high synchronicity experiences a high abnormal momentum return (Chen & Doukas, 2020). Since the momentum anomaly has characteristics like those to PEAD, there is reason to believe that stock price synchronicity is a potential driver of PEAD.

3.4. Research gap and hypotheses development

To summarize, the empirical evidence of PEAD remain one of the great puzzles to academia as it continues to question the efficient market hypothesis. The phenomenon has been studied over 30 years, across capital markets and with numerous different research designs. Most evidence have pointed towards the anomaly being persistent independently of development stage and size of capital market. Nonetheless, a smaller number of studies that focus on smaller, yet well developed markets and in these cases the existence of PEAD is more uncertain. Researched markets contradicting the larger stream of literature currently consist of the capital markets of Finland, Belgium as well as Sweden, where the existence of PEAD have both been documented and rejected during the last 15 years. Furthermore, the research designs of the Swedish studies diverge in their estimation for earnings surprises, which resembles the overall literature with indefinite modifications and approaches possible, rather than one single established methodology. As presented in the empirical evidence, historical-figures, analyst forecasts, stock returns and combinations of all three have been used in the wider PEAD literature as the basis for estimating earnings surprises. Together with the wide literature that study the persistence of PEAD across markets and time, is the equally extensive literature that try to explain the underlying factors that drive the drift. Early explanations stem from the fact that the sign and magnitude of the drift is associated with the autocorrelation of earnings between quarters and many studies document the impact of investor behavior and characteristics. Investor attention, level of sophistication, information processes biases, overreactions to announcements and ability to understand financial reports in a correct and timely matter, all present possible explanatory factors in the literature. Other factors include more firm-specific information, liquidity risk and transaction costs. A common denominator for the drivers is the information uncertainty in disclosures and the information noisiness in the market. The level of noisiness can be quantified with a variety of measures, where common proxies consist of bid-ask spread, trading volume and analyst coverage and dispersion. Stock price synchronicity is a fourth holistic measure that captures firm-specific information noisiness. The advantage of using such measure is that it aims to capture all information noisiness based on the cumulative market reaction, in contrast to the other mentioned measures which present more specific elements of information noisiness. Stock price synchronicity is negatively correlated with accounting quality, and recent studies find that the momentum anomaly can partially be explained by stock price synchronicity, where firms with high synchronicity experiences a high abnormal momentum return. Since the momentum anomaly is closely related to PEAD, there is reason to want to explore its relationship to PEAD as well. Thus, this study aims to contribute to the current PEAD literature by answering the question:

Is there a post-earnings announcement drift in the Swedish capital market and can it be explained by information noisiness?

With this question, the contribution to the literature is threefold. First, the Swedish stock market is a small, well-established market, yet it is a capital market with limited research in the area. The current evidence on the Swedish market alone presents current contradictions, since Setterberg (2011) finds a significant drift over a 12-month period while a more recent unpublished study by Karlsson & Jeganmohan (2020) do not find any drift. Further, there is great divergence in the methods used to measure and study PEAD, especially in regard to the estimation of earnings surprises. To date, no study has covered and compared all four most common methodologies, which is done in this paper. The Swedish market has been investigated solely through the two historical figure approaches, and thus this study introduces two new methodologies to the market. Last, we complement to the stream of literature that tries to explain the drift by examining if stock price synchronicity can partially explain PEAD.

Given that the vast majority of the recent literature still observe a drift, and the evidence presented by Setterberg (2011) of a strong and significant drift in the Swedish market, there is reason to believe that PEAD is still present in the market. Nonetheless, we acknowledge the strong possibility that the drift has decreased in persistence and magnitude since then, due to the wider spread of knowledge of the anomaly and the increase in availability of high-quality firm-specific information to investors, but that the attenuating effects are not substantial enough to reduce the drift to null. Thus, the first hypothesis is:

H1: There is a post-earnings announcement drift on the Swedish stock market

Information uncertainty and level of information noisiness appear to present explanatory value to stock market anomalies, such as the momentum anomaly where high momentum is associated with high levels of stock price synchronicity. Further, the measure is found to be negatively correlated with high financial disclosure quality, while as poor disclosure quality is documented to be a driver of PEAD. Thus, these two findings give reason to believe that stock price synchronicity could present a more holistic explanatory driver of the drift, where a higher stock price synchronicity is associated with a higher PEAD. Thus, the second hypothesis is:

H2: A high level of firm-specific stock price synchronicity is an underlying driver of the post-earnings announcement drift in the Swedish stock market

4. Data and descriptive statistics

The sample in this study is based on non-financial firms listed on the Nasdaq Stockholm Stock Exchange in the time period of 2002 – 2019. The data used is collected from multiple databases. First, the firm characteristics of all firms on a quarterly basis is collected from the database Compustat Global. Second, the announcement dates of the quarterly reports are retrieved from Thomson Reuters Datastream which is a part of the database Eikon. The database does not provide sufficient data of the announcement dates of reports prior to 2002, thus this presents the lower time limit of our study. Further, analyst forecast figures available for the time period 2002 – 2019 are retrieved through the Eikon database, where the original source of the forecasts is I/B/E/S.

Daily closing dividend-adjusted stock prices and quarterly market capitalization figures are collected from the database FinBas. Further, Fama-French three-factor model data based on the FinBas database are collected from the datacenter provided by the Swedish House of Finance (SHoF), where the most recent year with sufficient data on daily figures is 2019. Thus, 2019 is the final year of our sample. In the SHoF database, the one-month Swedish Treasury bill rate is used as proxy for the risk-free interest rate. In addition, the SIX Return Index is used as proxy for the return on the market, which is a value-weighted index of all stocks on the Stockholm Stock Exchange. All variable names can be found in appendix 9.

The full sample consists of 618 unique firms and 16,122 firm-quarter observations. The sample size has different levels of reductions depending on the method used to estimate the earnings surprise and the availability of the required data. The sample with the time-series model have a total of 404 unique firms with 9,271 observations, the sample with seasonal martingale model have a total of 573 unique firms with 14,087 observations, the sample with analyst forecasts have a total of 366 unique firms and 5,175 observations and the sample with event-window return have the total 618 unique firms with 16,122 observations. In the robustness tests of this paper all regressions are performed on a common sample across all methodologies for comparability, see section 7.2.2. Table 3 below presents descriptive statistics for our full sample and appendix 8 presents descriptive statistics for the individual samples.

Table 3. Descriptive statistics of firm characteristics for the full sample

Variables	N	Mean	Median	Std. Dev.	Skewness	Kurtosis
Assets	16,091	10,118	640	35,341	6.69	58.29
Debt	16,090	6,041	299	22,681	8.01	87.43
Equity	16,091	3,984	305	13,762	6.25	49.19
Market Cap	16,122	10,409	691	37,267	6.97	63.83
M/B	16,042	8.08	2.43	33.32	12.25	136.21
Debt/Equity	16,090	1.73	1.04	4.66	12.73	130.81
Debt/Assets	16,090	0.49	0.51	0.24	4.71	113.92

Note: descriptive statistics for the full sample of 618 firms listed on the Nasdaq Stockholm Stock Exchange between 2002 and 2019. All accounting variables are measured at the end of each quarter. Market cap is measured as the closing market capitalization on the last day of the quarter. M/B is the market cap divided by the book value of owners' equity. All values in MSEK.

The average asset base (*Assets*) of the firms in our sample is approximately 10,000 MSEK, which is largely driven by a smaller number of very substantially larger firms, as the median for the sample only amounts to 640 MSEK. The same relation can be observed for the average and median market capitalization (*Market Cap*), *Debt* and *Equity* of the firms. Noteworthy is that equity has a less prominent percentual difference between mean and median relative to the other metrics. This indicates that the largest firms are more levered than the rest of the sample but is also an effect from some firms having negative equity (approximately 1% of the observations).

5. Research Design

The research design used in this paper is an event study design, where the risk-adjusted abnormal return is investigated over a period after quarterly earnings announcements. The overall research design follows previous studies of PEAD. Foremost, this study follows the original study by Bernard and Thomas (1989), as well as Setterberg (2011) to create comparable results for the Swedish market. The estimation of additional earnings surprise measures follows Ayers et al. (2011), Liu et al. (2003), and Livnat & Mendenhall (2006). For the stock price synchronicity estimation, we follow Chen & Doukas (2020) which in turn follow the early pioneers within the field (Durnev et al., 2003).

5.1. Earnings surprise

As stated in equation 2, the earnings surprise in its most general form is defined as the difference between actual earnings and expected earnings. Hence, to be able to quantify the level of earnings surprise, one must estimate the expectation. As discussed previously, several methods for estimating earnings exists. In this paper, we use a time-series model (following Setterberg, 2011), a seasonal martingale model (following Ayers et al., 2011), analyst forecast estimation (following Ayers et al., 2011; Livnat & Mendenhall, 2006) and event-window return estimation (following Liu et al., 2003) to calculate the earnings surprise. Like most previous studies, we use earnings per share (EPS) as our earnings metric, defined as net income divided by the number of outstanding ordinary shares.[3] Hereafter, we describe the calculation process for estimating the earnings surprises for each of the different methodologies.

5.1.1. Time-series estimation (TS)

In the time-series estimation procedure (TS), the goal is to predict how EPS will develop based on the historical development of EPS, where the seasonal change in corresponding quarters

[3] In this study, the terms EPS and earnings is used interchangeably.

between years is considered, i.e., the change in earnings between Q1 in year 1, and Q1 in year 2 and Q1 in year 3. Since this is the only method previously used to calculate earnings surprise in a Swedish setting (Setterberg, 2011), we follow this study in full in the TS estimation process, with the exception of using EPS instead of net income, which was used as the earnings metric. However, in Setterberg (2011) it was stated that it would be preferrable to use EPS, as it is more relatable to stock prices and the foremost used metric used in the literature but due to the limited data available it was not rational to select it at the time. Currently, the data availability is equivalent for EPS and net income and thus EPS is used.

To start, we use a first autoregressive model to estimate the change in EPS based on the previous development of EPS. Thus, last year's change in EPS is regressed on the preceding year's change in EPS, as follows:

$$EPS_{i,t} - EPS_{i,t-4} = \alpha_i + \beta_{i,t} * \left[EPS_{i,t-4} - EPS_{i,t-8}\right] + \varepsilon_{i,t} \tag{11}$$

where:
$EPS_{i,t}$ = reported earnings per share of firm *i* in quarter *t*
α_i = firm-specific intercept
$\beta_{i,t}$ = autoregressive term for firm *i* in quarter *t*
$\varepsilon_{i,t}$ = residual term for firm *i* in quarter *t*

The beta for each firm-quarter observation is estimated over the sample period using a rolling window of the last nine quarters, and expected seasonal differences are predicted based on the betas. The expected seasonal difference is then used to calculate expected EPS as follows:

$$E_{t-1}^{TS}\left[EPS_{i,t}\right] = EPS_{i,t-4} + E_{t-1}\left[\Delta EPS_{i,t}\right] \tag{12}$$

where:
$E_{i,t-1}^{TS}[\dots]$ = expected value of $[\dots]$ for firm *i* in quarter *t-1* based on time-series prediction
$EPS_{i,t}$ = actual earnings per share for firm *i* in quarter *t*
$\Delta EPS_{i,t}$ = change in earnings per share between quarter t and t-4, i.e., the seasonal difference

The unexpected earnings in then defined as the difference between reported EPS and expected EPS. The earnings surprise is scaled by the standard deviation of the expected earnings for the firm, in line with procedure of Setterberg (2011). The rationale behind this scaling is that low standard deviation implies high certainty and thus a larger emphasize should be put on such earnings surprises. Further, as the underlying driver of the standard deviation is changes in EPS, one can interpret this as that earnings surprises in firms with generally more stable reporting, should be more surprised when there is a divergence. In total, the surprise measure standardized unexpected earnings (SUE) is calculated as:

$$SUE_{i,t} = \frac{EPS_{i,t} - E_{t-1}^{TS}\left[EPS_{i,t}\right]}{\sigma_i} \tag{13}$$

where:
$SUE_{i,t}$ = standardized unexpected earnings for firm *i* in quarter *t*
$EPS_{i,t}$ = actual earnings per share for firm *i* in quarter *t*
$E_{i,t-1}^{TS}[\ldots]$ = expected value of [...] for firm *i* in quarter *t-1* based on time-series estimation
$\sigma_{i,t}$ = standard deviation of expected earnings per share for firm *i*

The estimated SUE from the time-series estimation is used to divide the full sample into portfolios, which is described in section 5.2. The descriptive statistics from the earnings surprise estimation is presented in table 4a. Here, the number of observations is less than for the full sample, which is an effect from the need of nine preceding quarters to be able to estimate EPS. Hence, the first years in the full sample is excluded as well as the first years for new firms when included. Further, if there is a gap in the sample, it affects the nine following quarters as no gaps is accepted in the estimation process.

Table 4a. Descriptive statistics of earnings estimates using TS (SEK)

Variables	N	Mean	Std. Dev.	Min	Max
Reported EPS	9,255	0.434	1.975	-34.37	16.46
Expected EPS	9,255	0.481	2.176	-34.95	24.72
Unexpected EPS	9,255	-0.047	2.353	-44.79	36.30
SUE	9,255	-0.354	1.583	-40.93	7.18

Note: Reported EPS, Expected EPS, Unexpected EPS and SUE estimates based on the time-series modell where Unexpected EPS is Expected EPS subtracted with Reported EPS. SUE is Unexpected EPS divided by firm-specific standard deviation in Expected EPS.

5.1.2. Seasonal martingale estimation (MG)

To be able to make a comparison between the different methodologies used in the PEAD literature, the seasonal martingale procedure (MG) is used in this study due to its straight-forward design and its frequent use within the literature. Seasonal refers to quarterly EPS being compared with the EPS from the corresponding quarter from the previous year, rather than the last quarter. Further, similar to the TS estimation, the earning surprise is scaled to get better comparability between firms. For the MG estimation, the surprise is scaled by the opening stock price (following Ayers et al., 2011). This procedure is used to standardize the earnings surprise to make it comparable between firms, as earnings are presented on a per share basis. The closing price for the previous quarter is the last figure without overlap with the investigated period, which is used to avoid biases. In total, the standardized unexpected earning (SUE) is calculated as follows:

$$SUE_{i,t} = \frac{EPS_{i,t} - EPS_{i,t-4}}{P_{i,t-1}} \tag{14}$$

where:
$SUE_{i,t}$ = standardized unexpected earnings for firm *i* in quarter *t*
$EPS_{i,t}$ = reported earnings per share of firm *i* in quarter *t*
$P_{i,t-1}$ = closing stock price for firm *i* in quarter *t-1*

The estimated SUE from the MG procedure is used to divide the full sample into portfolios, which is further explained under section 5.2. The descriptive statistics for the earnings surprise estimation is presented in table 4b One may note that the expected EPS fluctuates more than reported EPS, which stems from the most extreme values in EPS were reported when stock prices were not available for the previous quarter. This creates a missing SUE and in turn the observation is excluded.

Table 4b. Descriptive statistics of earnings estimates using MG (SEK)

Variables	N	Mean	Std. Dev.	Min	Max
Reported EPS	13,792	0.318	2.219	-49.26	16.46
Expected EPS	13,792	0.230	2.618	-51.33	40.74
Unexpected EPS	13,792	0.092	2.569	-49.59	49.61
SUE	13,792	0.013	0.432	-15.49	28.43

Note: Reported EPS, Expected EPS, Unexpected EPS and SUE estimates based on the seasonal Martingale model where Unexpected EPS is Expected EPS subtracted with Reported EPS and SUE is Unexpected EPS divided by closing stock price for the firm previous quarter.

5.1.3. Analyst forecast estimation (AF)

To obtain the earnings surprise with the help of analyst forecast estimation (AF), the expected earnings is based on estimates reported by analysts. In this paper, the median estimate of earnings per share from I/B/E/S is used as the proxy for expected earnings which is then compared with actual earnings to obtain the earnings surprise, following Ayers et al. (2011). This is scaled with the closing stock price from the previous quarter to obtain SUE, as follows:

$$SUE_{i,t} = \frac{EPS_{i,t} - E_{i,t}^{AF}[EPS_{i,t}]}{P_{i,t-1}} \tag{15}$$

where:
$SUE_{i,t}$ = standardized unexpected earnings for firm *i* in quarter *t*

$EPS_{i,t}$ = reported earnings per share of firm *i* in quarter *t*
$E_{i,t}^{AF}[...]$ = expected value of [...] for firm *i* in quarter *t* based on analyst forecast
$P_{i,t-1}$ = closing stock price for firm *i* in quarter *t-1*

The estimated SUE from the AF estimation is used to divide the full sample into portfolios, which is further explained under section 5.2. The descriptive statistics from the earnings surprise estimation is presented in table 4c (see below). The number of observations in the sample is the lowest for this method compared to the others due to the limited amount of analyst forecasts.

Table 4c. Descriptive statistics of earnings estimates using AF (SEK)

Variables	N	Mean	Std. Dev.	Min	Max
Reported EPS	5,175	0.690	2.894	-51.58	16.66
Expected EPS	5,175	0.972	1.621	-17.24	19.13
Unexpected EPS	5,175	-0.138	2.001	-53.36	16.98
SUE	5,175	-0.008	0.215	-8.26	11.50

Note: Reported EPS, Expected EPS, Unexpected EPS and SUE estimates based on analyst forecasts where Unexpected EPS is Expected EPS subtracted with Reported EPS.

5.1.4. Event-window return estimation (RB)

To calculate the earnings surprise with the event-window return estimation (RB), we follow the procedure by Liu et al. (2003). They calculate the earnings surprise as the buy-and-hold abnormal return (BHAR) of each firm over the market return from -1 to +2 days around the earnings announcement. In the cases where the event window coincides with a weekend or bank holiday, the nearest following trading day have been used. As this paper uses +2 days as the starting point of the holding period, we exclude the last day to avoid overlap and to make the results from the different methodologies more comparable. Hence, the earnings surprise, estimated as abnormal event-window return (AEWR), is calculated as:

$$AEWR_{i,t} = \prod_{d=-1}^{1}\left(1 + R_{i,d}\right) - \prod_{d=-1}^{1}\left(1 + R_{m,d}\right) \tag{16}$$

where:
$AEWR_{i,t}$ = unexpected earnings for firm *i* quarter *t*
$R_{i,d}$ = return for security *i* on day *d*, where $d = 0$ is the earnings announcement date
$R_{m,d}$ = market return on day *d*, where $d = 0$ is the earnings announcement date

The AEWR from the RB estimation is used to divide the full sample into portfolios, which is further explained under section 5.2. The descriptive statistics from the earnings surprise estimation is presented in table 4d. This method generates the largest sample across the methods, as the calculation does not require anything else than stock price data and announcement dates.

Table 4d. Descriptive statistics of earnings estimates using RB (SEK)

Variables	N	Mean	Std. Dev.	Min	Max
Reported EPS	16,317	-0.066	3.895	-52.01	16.73
AEWR	16,317	-0.001	0.105	-0.60	6.52

Note: Reported EPS is the reported earnings per share in the announcement. AEWR is the abnormal BHAR during the event window.

5.2. Portfolio formation

To distinguish differences in long-term abnormal returns across earnings surprises, the announcements for each quarter are divided into portfolios based on the magnitude of the surprise. First, we do a distinction between positive earnings surprises (SUE/AEWR ≥ 0) and negative earnings surprises (SUE/AEWR < 0). This is done to get homogenous signals in each portfolio as some quarters are substantially skewed with a majority of positive or negative surprises, which otherwise would create portfolios with mixed signals. The reasoning rests on the assumption that a positive surprise is always good news, irrespective of the performance of other firms in the same quarter. The main drawback of this decision is that the portfolios vary in size if there are more of either positive or negative surprises. Next, we divide the respective subsample of positive and negative surprises into 5 equally sized portfolios, yielding a total of 10 portfolios where 1-5 (6-10) are negative (positive) surprises and 1 (10) is the most prominent negative (positive) surprise. Each portfolio is equally weighted with its firms, as the sample consists of a few vary large firms that would otherwise impact the results significantly. Further, it would yield a simpler trading strategy which does not have to take market capitalization into consideration. However, the drawback of such choice is that there will be a bias towards small firms, which may impact the results as previous studies have concluded a more prominent drift among smaller firms.

To maintain a high number of observations for our first hypothesis across all methodologies and to be able to divide each portfolio in two for the test of our second hypothesis, we merge the portfolios to keep a reasonable sample size within each new portfolio throughout the whole study. This yields 5 portfolios, where initial portfolios 1 and 2 together represent portfolio 1 and so on, see figure 3 below for illustration. As a robustness test to this choice, we perform regressions based on a division of 10 portfolios as well, the results are discussed in section 7.2.3. in the analysis and regression tables can be found in appendix 2. Henceforward, only the extreme portfolios 1 and 5 will be of interest, as these portfolios are the once used to execute the PEAD strategy. Descriptive statistics for reported EPS, expected EPS and earnings surprise measure for portfolio 1 and 5 across all methods can be found in appendix 1.

<table>
<tr><td rowspan="5">Positive earnings surprise
(SUE/UE ≥ 0)</td><td>Portfolio 10</td><td rowspan="2">Portfolio 5 (Positive)</td></tr>
<tr><td>Portfolio 9</td></tr>
<tr><td>Portfolio 8</td><td rowspan="2">Portfolio 4 (Positive)</td></tr>
<tr><td>Portfolio 7</td></tr>
<tr><td>Portfolio 6</td><td rowspan="2">Portfolio 3 (Uncertain)</td></tr>
<tr><td rowspan="5">Negative earnings surprise
(SUE/UE < 0)</td><td>Portfolio 5</td></tr>
<tr><td>Portfolio 4</td><td rowspan="2">Portfolio 2 (Negative)</td></tr>
<tr><td>Portfolio 3</td></tr>
<tr><td>Portfolio 2</td><td rowspan="2">Portfolio 1 (Negative)</td></tr>
<tr><td>Portfolio 1</td></tr>
</table>

Figure 3. Portfolio formation process

5.3. Post-earnings announcement drift test design

To test for PEAD, we investigate if any abnormal return can be earned by taking a long position in the portfolio with the most positive surprises (hereafter LONG), a short position in the portfolio with the most negative surprises (hereafter SHORT), or the combination of these two positions (hereafter PEAD-position). To examine PEAD after the earnings announcements, we use an event-time based approach. As a first test of PEAD, we use a market-based BHAR as measure of abnormal return measured over the succeeding 12-month period. To assess the significance, a regression model based on monthly alpha is set up for 4 specific holding periods of 1, 3, 6 and 12 months, where the excess return for the LONG, SHORT and PEAD-position is controlled for with the Fama-French 3-factors market risk premium, SMB and HML.

5.3.1. Event window and holding period

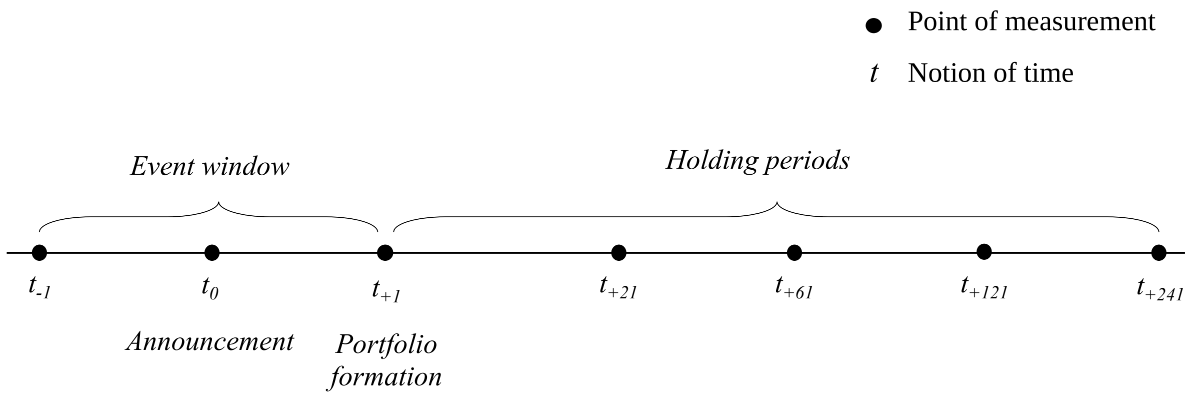

Figure 4. Event study design

In this paper we perform event-time portfolio formation, where all positions are taken in relation to the earnings announcements rather than simultaneously (as in the calendar-time methodology). The event-based approach is more theoretically correct as we start measuring the drift immediately after the event, rather than with the delay of waiting for all announcements to occur, which brings the results of this paper close to investigate the firm-specific drift. The argument for using the calendar-time methodology is that it is more implementable as one does not need to know ex-ante which portfolio each firm belongs to. However, this must be weighed against the fact that firms report over a period which make the impact on portfolio return from each firm irregular, especially over shorter holding periods.

The event-window is defined as ± 1 day around the earnings announcement. The day after announcement is usually included as reports may be released in the evening and the initial reaction thus appears the day after. The day preceding the announcement is included as previous studies show that a reaction often occurs already that day, which is interesting but outside the scope of this paper. For robustness tests, the event window is expanded to + 5 days succeeding the announcement date as well. In turn, the position is taken at closing 1 day after announcement and held for 1, 3, 6 and 12 months, where one month is defined as 20 trading days (yields holding periods of 20, 60, 120 and 240 days). Generally, early studies have had longer holding periods, up to 12 months, whereas more recent studies have had shorter periods of approximately 2-3 months (see table 1). This study is conducted with multiple holding periods of varying length to obtain as extensive results as possible for the market, further motivated with the previous results on the Swedish market by Setterberg (2011), where PEAD is only significant for a 12-month period.

5.3.2. BHAR

As a first step to investigate if there is a PEAD in the market, the BHAR methodology is used with a market-based model, that is compared to the performance of a value-weighted index on all firms. The firm specific BHAR is based on daily returns and is compounded over holding periods from 1 until 12 months, based on 20 trading days per month, as:

$$BHAR_{i,q,T} = \prod_{t=2}^{T} \left(1 + R_{i,t}\right) - \prod_{t=2}^{T} \left(1 + R_{m,t}\right) \tag{17}$$

where:
$BHAR_{i,q,T}$ = buy-and-hold abnormal return for firm *i* from announcement of quarter q over holding period T
t = number of days after quarterly earnings announcement
T = holding period in days after earnings announcement. T = 21, 41, 61, …, 241.
$R_{i,t}$ = one day return for firm *i* at day t
$R_{m,t}$ = one day return for the market at day t

When the portfolio BHAR are calculated, the firms are equally weighted and is thus calculated as:

$$BHAR_{p,q,T} = \frac{1}{N}\sum_{i=1}^{N} BHAR_{i,q,T} \tag{18}$$

where:
$BHAR_{p,q,T}$ = buy-and-hold abnormal return for portfolio p for quarter q over holding period T
$BHAR_{i,q,T}$ = buy-and-hold abnormal return for firm *i* from announcement of quarter q over holding period T
N = number of firms in portfolio p

When presented, portfolios 1 (SHORT) and 5 (LONG) are included together with the hedge position (denoted PEAD-position) to see what a zero investment would yield from a strategy of buying the most positive surprising firms financed by selling the most negatively surprising. We use BHAR as it gives a realistic picture of the performance since it is aligned with investor behavior in practice, where a position is taken and held, rather than the position being rebalanced continuously. Further, when several holding periods are investigated, it is convenient to keep track of the performance over the different periods which alleviate the problem with compounding. With the market return as the benchmark, the BHAR metric gives a direct indication of whether the firm or portfolio overperforms the market. In turn, if one assumes that earnings surprises happen equally distributed across the market, so that no risk factor is related to the earnings surprise and market beta for each portfolio in expectation equals unity, then BHAR is a measure for PEAD. We do this as a first indication of whether a PEAD exist, and we introduce risk-factors in the next section.

5.3.3. Risk adjustment and final regression models

To control that the observed BHAR is not just an effect of priced risk, we use the methodology of monthly alphas to assess the significance of the drift. We include the Fama-French factors for size (*SMB*) and the value premium (*HML*), as well as the market premium (*RMRF*), in line with most recent studies (see table 1). Daily returns as well as daily risk premiums for each factor are compounded monthly based on the event dates and are equally weighted into monthly portfolio returns and factors based on the portfolio formation in section 5.2. The regression for the LONG portfolio is thus specified as:

$$\begin{gathered} R_{LONG,q,t} - Rf_{LONG,q,t} = \alpha_{p,q} + \beta^{RMRF} * RMRF_{LONG,q,t} + \beta^{SMB} * SMB_{LONG,q,t} \\ +\beta^{HML} * HML_{LONG,q,t} + \varepsilon_{q,t} \end{gathered} \tag{19}$$

where:
$R_{LONG,q,t}$ = monthly return for portfolio LONG with formation quarter q in month t
$Rf_{LONG,q,t}$ = average monthly risk-free rate in portfolio LONG with formation quarter q in month *t*
$RMRF_{LONG,q,t}$ = average market risk premium in portfolio LONG with formation quarter q in month *t*
$SMB_{LONG,q,t}$ = average monthly risk premium for low over high market cap stocks in portfolio LONG with formation quarter q in month *t*
$HML_{LONG,q,t}$ = average monthly risk premium for high B/M stocks over low B/M stocks in portfolio LONG with formation quarter q in month *t*

Further, the regression for the SHORT portfolio is specified as:

$$R_{SHORT,q,t} - Rf_{SHORT,q,t} = \alpha_{p,q} + \beta^{RMRF} * RMRF_{SHORT,q,t} + \beta^{SMB} * SMB_{SHORT,q,t} + \beta^{HML} * HML_{SHORT,q,t} + \varepsilon_{q,t} \tag{20}$$

where:
$R_{p,q,t}$ = monthly return for portfolio SHORT with formation quarter q in month t
$Rf_{p,q,t}$ = average monthly risk-free rate in portfolio SHORT with formation quarter q in month *t*
$RMRF_{p,q,t}$ = average market risk premium in portfolio SHORT with formation quarter q in month *t*
$SMB_{p,q,t}$ = average monthly risk premium for low over high market cap stocks in portfolio SHORT with formation quarter q in month *t*
$HML_{p,q,t}$ = average monthly risk premium for high B/M stocks over low B/M stocks in portfolio SHORT with formation quarter q in month *t*

The regressions are performed over the different holding periods, 1, 3, 6 and 12 months, where the regressions include the months up until each holding period. Hence, the regressions for the 12-month holding period will include 12 times the number of observations as the regressions for the 1-month holding period. The portfolios included in the regressions are portfolio 1 (denoted SHORT) and portfolio 5 (denoted LONG) as well as regressions for the PEAD-position. In the regressions on the PEAD-position, the dependent variable is calculated as:

$$R_{PEAD,q,t} = R_{LONG,q,t} - R_{SHORT,q,t} \tag{21}$$

where:
$R_{PEAD,q,t}$ = monthly return for PEAD-portfolio with formation quarter q in month t
$R_{LONG,q,t}$ = monthly return for portfolio LONG with formation quarter q in month t
$R_{SHORT,q,t}$ = monthly return for portfolio SHORT with formation quarter q in month t

Thus, it is implied that the risk-free rate is assumed to be equal for the corresponding formation quarter in the LONG and SHORT portfolio. This assumption is done also for the risk factors included in the assessment of the significance of the PEAD-position, where the factor premiums from the LONG position is used. The shortcomings of this choice are discussed in the next paragraph. The regression for the PEAD-portfolio is specified as:

$$R_{PEAD,q,t} = \alpha_q + \beta^{RMRF} * RMRF_{LONG,q,t} + \beta^{SMB} * SMB_{LONG,q,t} + \beta^{HML} * HML_{LONG,q,t} + \varepsilon_{q,t} \tag{22}$$

where:
$R_{PEAD,q,t}$ = monthly return for portfolio LONG with formation quarter q in month t less monthly return for portfolio SHORT with formation quarter q in month t (see equation 21)
$RMRF_{LONG,q,t}$ = average market risk premium in LONG portfolio with formation quarter q in month *t*
$SMB_{LONG,q,t}$ = average monthly risk premium for low over high market cap stocks in LONG portfolio with formation quarter q in month t
$HML_{LONG,q,t}$ = average monthly risk premium for high B/M stocks over low B/M stocks in LONG portfolio with formation quarter q in month *t*

As previously discussed, the event-time methodology is generally preferred as it is more theoretically sound as the drift is investigated in relation to its announcement which ultimately is of main interest. The backside of the setting is that the portfolios become highly theoretical, as the monthly performances stem from different time periods for each firm. This also holds for the risk factors, as the risk premiums are compounded based on the announcement dates of the holdings in the portfolios. This could potentially affect their explanatory power. However, as earnings announcements are focused to a few weeks every year, the negative impact from this theoretical approach should be limited. Similarly, the choice of using the factor premiums estimated for the LONG portfolio (rather than, for example, the SHORT or the mean of the two) should not impact the results significantly as there is no reason to believe that announcement dates for positive and negative surprises should differ.

We perform the regressions with the calendar-time methodology in section 7.3 in the analysis, mainly to ensure that a potential theoretical abnormal return would be possible to earn with an implementable trading strategy. When this is done, the potential problem with the skewed factor loading is simultaneously solved for to ensure that the results are not affected by this choice of methodology. Another potential solution would be to do the regressions on firm level rather than portfolios by quarter. The drawback of such setup would be that the results would be more affected by observations in recent years as the number of firms have increased over the years. Further, it is preferred to investigate the portfolio performance on an aggregate level as that is how a strategy based on earnings surprises would be implemented.

5.4. Stock price synchronicity test design

For the second hypothesis, we test whether information noisiness influences the level of PEAD. The overall approach is to estimate stock price synchronicity follows Chen & Doukas (2020) and Durnev et al. (2004). The structure of integrating this variable to our PEAD research design follows Francis et al. (2007) which tested if information uncertainty is a driver of PEAD.

5.4.1. The stock price synchronicity variable

To estimate the proxy for information noisiness, stock price synchronicity, firm specific return is regressed on the return for the market and the industry. Both market and industry returns are based on value-weighted returns, where industries are classified using the two-digit General Industry Classification (GIC), obtained from Eikon. We apply weekly returns as daily returns is found too volatile, while monthly returns yield too few observations to obtain a reliable estimate and to be able to catch variations over time (Chen & Doukas, 2020; Durnev et al., 2004). To avoid hindsight bias, a rolling window of 51 weeks is used between 52 and 1 week preceding the earnings announcement. The regression is specified as follows:

$$R_{i,t} = \beta^0 + \beta^1 * R_{m,t} + \beta^2 * R_{I,t} + \varepsilon_{i,t} \tag{23}$$

where:
$R_{i,t}$ = weekly return for firm *i* at time *t*
$R_{m,t}$ = weekly value-weighted market return at time t
$R_{I,t}$ = weekly value-weighted industry return at time t based on two-digit GIC

The stock price synchronicity (*SPS*) obtained from the regression is the regressions R^2, i.e., the amount of fluctuation in firm specific return explained by the return of the market and its industry.

5.4.2. Portfolio formation and regressions

When the SPS is estimated for all firms in the full sample, three portfolios based on SPS are created for each quarter (denoted LOW, MEDIUM and HIGH). This is to timely match the portfolio formation based on earnings surprise and to avoid bias from structural changes in SPS over time. Three portfolios are used to be able to exclude a middle and ensure a clear deviation in SPS between the two samples compared, following the method of Francis et. al., (2007) who use this method to test if firm's level of information uncertainty impact PEAD. Table 5 presents descriptive statistics for SPS across the full sample and the three portfolios based on SPS.

Table 5. Descriptive statistics of stock price synchronicity for the three subsamples

Sample	N	Mean	Median	Std. Dev.	Min	Max
Full sample	16,122	0.180	0.124	0.173	0.000	1.000
LOW	5,399	0.036	0.030	0.029	0.000	0.261
MEDIUM	5,373	0.135	0.123	0.062	0.028	0.353
HIGH	5,350	0.369	0.339	0.162	0.067	1.000

Note: the table presents the mean, median, standard deviation, min and max for stock price synchronicity (SPS) for the full sample and the three subsample of low, medium and high SPS.

It can be noted that there are overlaps in the portfolios, which implies that the general level of stock price synchronicity varies across quarters and strengthens the argument for a division per quarter rather than full sample. As a next step, based on the portfolios from SPS, the existing portfolios from the earnings surprise estimations are further divided into subsamples. When this is completed, the medium portfolio from the SPS division is excluded to ensure a clear deviation in SPS in the two subsamples from the same original earnings surprise. See figure 5 for visual description of this portfolio formation.

<table>
<tr><th>Full sample</th><th>Existing extreme portfolios</th><th>New portfolios</th></tr>
<tr><td rowspan="2">HIGH SPS</td><td rowspan="3">Portfolio 5 (Positive)</td><td>Portfolio 5 – HIGH</td></tr>
<tr><td>~~Portfolio 5 – MEDIUM~~</td></tr>
<tr><td rowspan="2">~~MEDIUM SPS~~</td><td>Portfolio 5 – LOW</td></tr>
<tr><td rowspan="3">Portfolio 1 (Negative)</td><td>Portfolio 1 – HIGH</td></tr>
<tr><td rowspan="2">LOW SPS</td><td>~~Portfolio 1 – MEDIUM~~</td></tr>
<tr><td>Portfolio 1 – LOW</td></tr>
</table>

Figure 5. Portfolio formation based on stock price synchronicity and extreme earnings surprise portfolios

Descriptive statistics for SPS and t-tests for the difference in SPS between the four new portfolios can be found in appendix 3, where we conclude that the new portfolios all have a significant difference in SPS. Next, we run the same regressions as the described in section 5.3.3. on the new portfolios. With the results for the subsamples separately, the goal is to be able to see clear differences in PEAD between the two. If the results align with the hypothesis, there will be a more prominent drift in the surprise portfolio with high SPS than in the corresponding surprise portfolio with low SPS.

6. Results

The result section is divided into two parts. First, we present the PEAD results on the Swedish market for all four earnings surprise methods separately followed by a final summary and comparison. Second, the regression results with stock price synchronicity as a potential driver are presented simultaneously for all methods together with a comparison and summary of the results.

6.1. Post-earnings announcement drift on the Swedish market

In this section, results from the BHAR calculations and the monthly alpha regressions are presented for each methodology of earnings surprises, time-series (TS), seasonal martingale (MG), analyst forecast (AF) and event-window return (RB). First, a graph over the BHAR over the 12-month period following the announcement is presented for the portfolios with the most positive earnings surprises (LONG), the negative earnings surprises (SHORT), and for the PEAD-position. Second, the regression results from equation 19, 20 and 22 are presented over the holding periods of 1, 3 and 12 months. The 6-month holding period have been excluded from the result tables as the results do not add any further insights or show significant results. For those methodologies where a drift is found in the shorter periods, i.e., 1- and 3-month holding periods, no drift is seen in the 6-month. Similarly, when a drift is found in the 12-month holding period, it is not found in the 6-month. The exception is when a drift is found throughout the holding periods, then it is also seen in the 6-month.

6.1.1. Time-series results

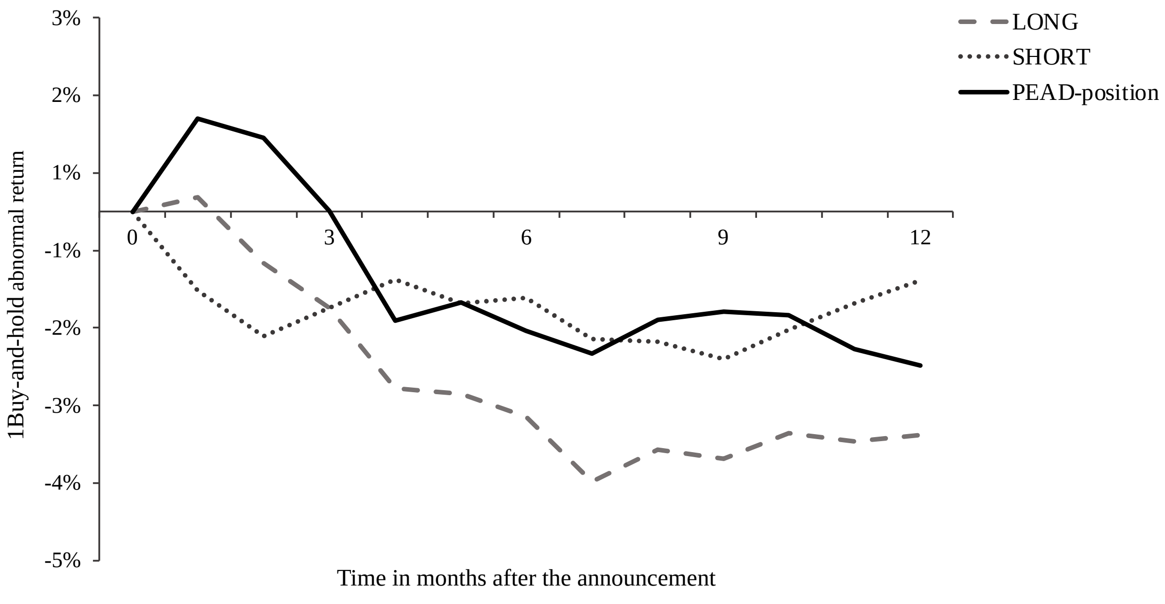

Figure 6a. Mean Buy-and-hold abnormal return (BHAR) after the announcement over the proceeding 12-month period with TS estimation for earnings surprise

Figure 6a shows the mean BHAR for SHORT, LONG and the PEAD-position for the TS methodology. The development after announcement does not mimic the classic pattern of the drift. The LONG portfolio experiences a positive drift only for the first month, and afterwards a substantial negative drift. The SHORT portfolio develops in the hypothesized direction initially, but the drift is observed only over the first two months before stabilizing for the remaining 12-month period. This yields a negative PEAD-position over most of the holding period. Thus, these results advocate for no existence of a drift in the market. As TS is the method used by Setterberg (2011), it is of extra interest to compare these results to those of her. Setterberg (2011) find the drift to be driven by the LONG portfolio, while her SHORT portfolio showed a similar pattern as the SHORT portfolio in this study. Thus, the difference in PEAD between these studies mainly stem from a shift in behavior of the LONG portfolio. Table 6a presents the results and coefficients of the regressions for the LONG, SHORT and PEAD portfolio for the holding periods of 1, 3 and 12 months, with control for the Fama-French three-factor variables, as specified in equation 19, 20 and 22.

Table 6a. Regression results with TS as estimation for earnings surprise

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.012**	-0.004	-0.000	-0.002	-0.003	-0.005**	0.0106	0.001	-0.004*
	(0.005)	(0.003)	(0.002)	(0.010)	(0.004)	(0.002)	(0.009)	(0.004)	(0.002)
RMRF	0.834***	0.851***	0.827***	0.922***	0.820***	0.969***	0.088	-0.031	0.142***
	(0.151)	(0.072)	(0.036)	(0.320)	(0.096)	(0.049)	(0.307)	(0.096)	(0.055)
SMB	0.130*	0.032	0.024**	0.128	0.010	0.029*	-0.002	-0.0224	0.004
	(0.066)	(0.028)	(0.012)	(0.141)	(0.036)	(0.016)	(0.135)	(0.036)	(0.018)
HML	-0.079**	-0.014	-0.000	-0.061	0.018	0.006	0.017	0.032	0.006
	(0.038)	(0.017)	(0.003)	(0.081)	(0.023)	(0.004)	(0.078)	(0.023)	(0.005)
N	58	174	696	58	174	696	58	174	696
R^2	0.426	0.494	0.480	0.169	0.351	0.412	0.011	0.014	0.016

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

In table 6a, we see results that confirms those of the previous BHAR graph. In the SHORT portfolio, there is an abnormal return of -1.2% at a 5% significance level when one month is considered, but not when more months are included. The LONG portfolio experiences a monthly abnormal return of -0.5% at a 5% significance level when the full holding period of 12 months is considered. This combination yields a negative return for the PEAD portfolio, where the 12-month holding period yields a monthly abnormal return of -0.4% at a 10% significance level. We may note that the factor with the most significance is *RMRF*, and no substantial difference in factor loading is seen between the portfolios. As observed in the BHAR graph, it is of interest to note that the difference in results compared to Setterberg (2011) mainly lays in the LONG position. In total, with the usage of TS to define earnings surprises, the results in this study point to a non-existence of a PEAD in the Swedish setting.

6.1.2. Seasonal Martingale results

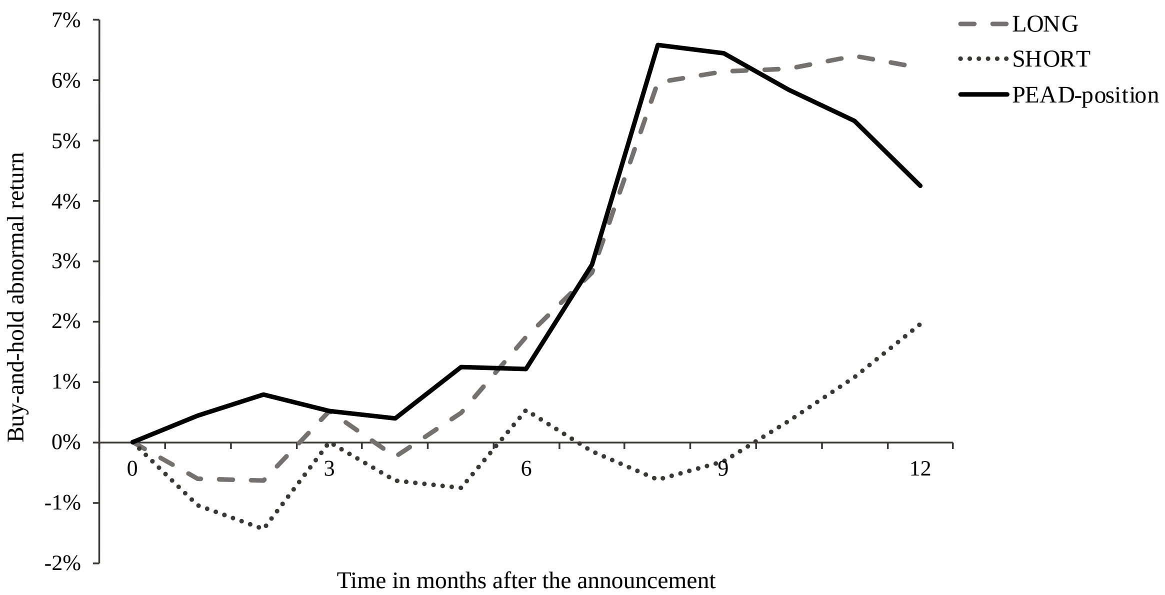

Figure 6b. Mean Buy-and-hold abnormal return (BHAR) after the announcement over the proceeding 12-month period with MG estimation for earnings surprise

With MG as earnings estimation approach, the BHAR graph in figure 6b reminiscences the results in Setterberg (2011) to a larger extent compared to the TS results. A drift is seen in the LONG portfolio over the full holding period, although most of it emerges after 6 months. In the study by Setterberg (2011), no significance is observed in the 6-month period but only for the 12-month, which aligns with figure 6b. In total, we observe a BHAR of approximately 4% over the full holding period for the PEAD portfolio. Table 6b presents the results and coefficients of the regressions with MG for the LONG, SHORT and PEAD portfolio for the holding periods of 1, 3 and 12 months, with control for the Fama-French three-factors, as specified in equation 19, 20 and 22.

Table 6b. Regression results with MG as estimation for earnings surprise

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.006	-0.002	-0.002	-0.009	-0.000	0.004	-0.003	0.001	0.007**
	(0.006)	(0.005)	(0.002)	(0.006)	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)
RMRF	0.735***	1.048***	0.992***	1.072***	0.905***	0.946***	0.306**	-0.137	-0.047
	(0.172)	(0.122)	(0.051)	(0.167)	(0.083)	(0.058)	(0.147)	(0.126)	(0.071)
SMB	-0.032	0.066	0.049***	0.128	0.093**	0.051**	0.165**	0.028	-0.000
	(0.093)	(0.055)	(0.018)	(0.091)	(0.038)	(0.020)	(0.079)	(0.057)	(0.025)
HML	0.008	-0.038	0.002	-0.099*	-0.049*	-0.007	-0.110**	-0.011	-0.008
	(0.059)	(0.042)	(0.004)	(0.058)	(0.029)	(0.005)	(0.051)	(0.043)	(0.006)
N	65	195	780	65	195	780	65	195	780
R^2	0.233	0.281	0.333	0.409	0.388	0.256	0.125	0.008	0.003

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

The results in table 6b do not confirm that the drift is driven by the LONG portfolio. Rather, we observe no significance in neither the LONG nor SHORT portfolio. However, for the full 12-month holding period, there is a monthly abnormal return of 0.7% at a 5% significance level in the PEAD portfolio. This emphasizes the tendencies there are within the LONG and SHORT portfolios, although they do not show significant results on a stand-alone basis. Furthermore, it is notable that the LONG position yields a negative abnormal return in the first month, although not significant. This lends some support to the findings of Milian (2015), where it was highlighted that the market tends to overreact to earnings surprises, due to the large awareness of the PEAD. In contrast to TS, the results from the MG approach yield a small indication that there is a PEAD in the Swedish market for a holding period of 12 months.

6.1.3. Analyst forecast results

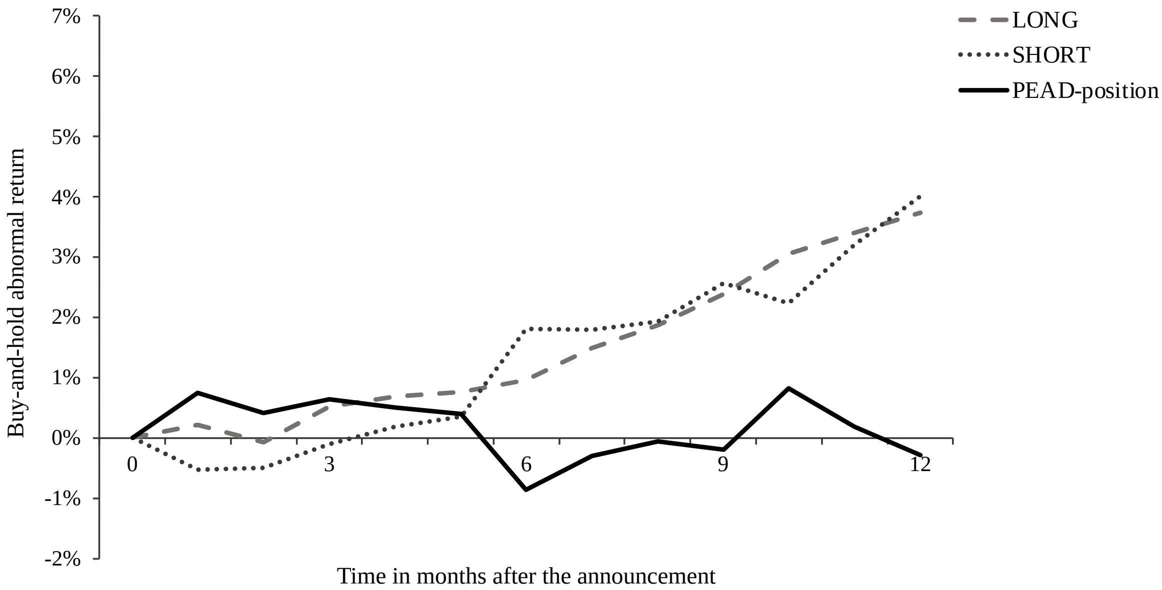

Figure 6c. Mean Buy-and-hold abnormal return (BHAR) after the announcement over the proceeding 12-month with AF estimation for earnings surprise

With AF, we note that both the LONG and SHORT portfolio give rise to a positive BHAR over the holding period (see figure 6c). Hence, the PEAD portfolio demonstrate no clear drift. These BHAR results contrast those seen in the previous methodologies and puts emphasize on the results dependence on the choice of methodology for estimating the earnings surprises. For example, we could almost see the direct inverse of this development in the BHAR graph for TS in figure 6a. Table 6c presents the results and coefficients of the regressions with MG for the LONG, SHORT and PEAD portfolio for the holding periods of 1, 3 and 12 months, with control for the Fama-French three-factors as specified in equation 19, 20 and 22 for the AF method.

Table 6c. Regression results with AF as estimation for earnings surprise

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.008*	-0.005*	-0.003*	0.001	0.002	0.000	0.009**	0.007**	0.003
	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)	(0.004)	(0.003)	(0.002)
RMRF	0.953***	1.045***	1.076***	1.234***	1.090***	1.063***	0.281**	0.045	-0.014
	(0.116)	(0.070)	(0.045)	(0.118)	(0.061)	(0.029)	(0.120)	(0.073)	(0.047)
SMB	0.071	0.028	0.036**	0.116	-0.008	0.009	0.046	-0.036	-0.027
	(0.077)	(0.030)	(0.016)	(0.078)	(0.026)	(0.010)	(0.079)	(0.031)	(0.016)
HML	-0.039	-0.011	-0.002	-0.069	0.008	0.004	-0.030	0.020	0.006
	(0.044)	(0.018)	(0.004)	(0.044)	(0.016)	(0.003)	(0.045)	(0.019)	(0.004)
N	60	180	720	60	180	720	60	180	720
R^2	0.556	0.569	0.454	0.671	0.654	0.658	0.095	0.011	0.006

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Surprisingly, the drift when risk-adjusted with Fama-French factors appear to be driven by a negative abnormal monthly return in the SHORT position, which stands in direct contrast to the results in the previous BHAR graph. 1-, 3- and 12-month holding periods all yield negative returns of 0.8%, 0.5% and 0.3% respectively, all at a 10% significance level. Further surprisingly is the non-existence of significant drift in the LONG position. However, there are tendencies of a positive abnormal monthly return in the LONG portfolio for 1- and 3-month holding periods, which yield an abnormal monthly return of 0.9 and 0.7% in the PEAD portfolio over the respective periods, at a 5% significance level, which provides support for PEAD in the market for the shorter holding periods. Additionally, it is notable that neither the *SMB* nor the *HML* factor appear to be drivers of the drift, as just the *SMB* factor over the 12-month holding period in the SHORT portfolio has a significant coefficient at the 5% significance level. In contrast, the *RMRF* is significant at 1% for all holding periods in the LONG and SHORT position. Thus, the performance of the portfolios is to a larger extent dependent on the market performance rather than other risk factors. This questions the assumption under the market-based BHAR methodology that the market beta of the portfolios equal unity.

6.1.4. Event-window return results

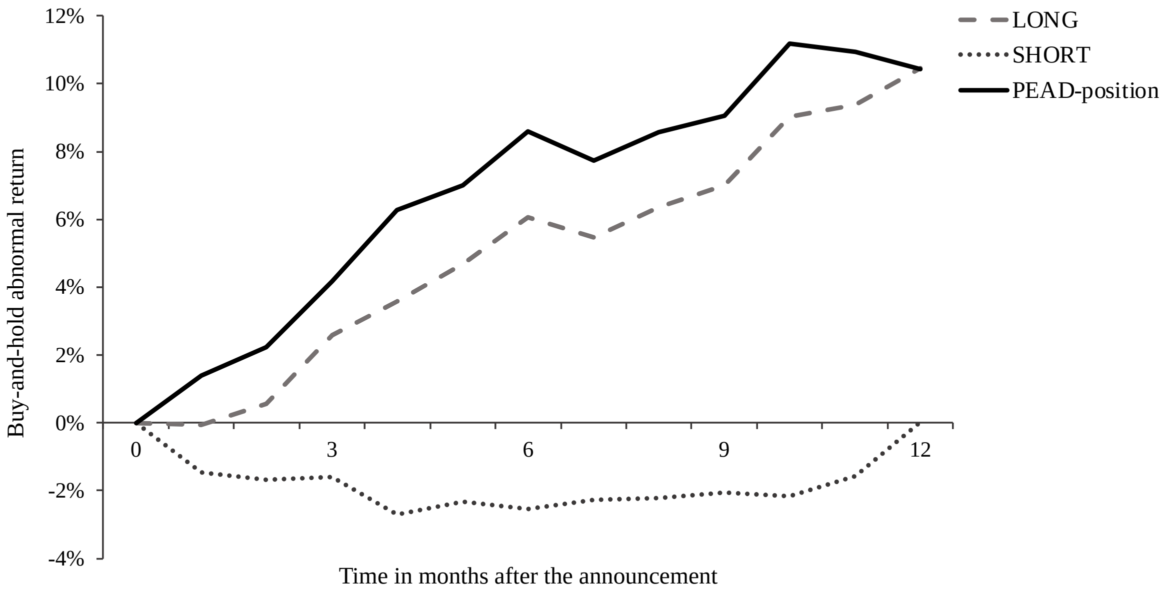

Figure 6d. Mean Buy-and-hold abnormal return (BHAR) after the announcement over the proceeding 12-month period with RB estimation for earnings surprise

Figure 6d presents the BHAR development for the RB portfolios. We observe a continuous positive drift for the LONG portfolio, although slower during the first months. The SHORT portfolio drifts slightly in the hypothesized direction in the first 4 months to then stabilize and revert to zero after the full 12-month holding period. Similar to the MG results and the results by Setterberg (2011), we see that the BHAR development for the PEAD-position in the long run is driven by the LONG portfolio. Table 6d presents the results and coefficients for the regressions for the LONG, SHORT and PEAD portfolio for all holding periods with controls for the Fama-French three-factors, for the RB method.

Table 6d. Regression results with RB as estimation for earnings surprise

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.024***	-0.009***	-0.004**	-0.001	0.009**	0.005**	0.023***	0.018***	0.009***
	(0.005)	(0.003)	(0.002)	(0.006)	(0.004)	(0.002)	(0.006)	(0.004)	(0.003)
RMRF	1.049***	0.896***	0.963***	0.715***	0.963***	0.971***	-0.335**	0.068	0.008
	(0.135)	(0.075)	(0.042)	(0.166)	(0.085)	(0.043)	(0.167)	(0.093)	(0.058)
SMB	0.152**	0.039	0.034***	0.098	-0.016	0.045***	-0.054	-0.055	0.010
	(0.069)	(0.029)	(0.012)	(0.085)	(0.033)	(0.012)	(0.086)	(0.036)	(0.016)
HML	-0.095**	-0.010	0.003	-0.065	-0.001	0.000	0.029	0.009	-0.002
	(0.042)	(0.022)	(0.003)	(0.052)	(0.025)	(0.003)	(0.053)	(0.027)	(0.005)
N	68	204	816	68	204	816	68	204	816
R^2	0.500	0.421	0.407	0.234	0.390	0.392	0.063	0.016	0.001

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

For RB, the indicative results from the BHAR graph holds when the Fama-French factors are considered to a large extent, where the most prominent difference is that the drift appear to stem from both the LONG and SHORT position. The initial reaction is more prominent for the SHORT position, where we observe an abnormal return of -2.4% at a 1% significance level while no significance is observed in the LONG position. Over the 3-month holding period, the monthly abnormal return is -0.9% for the SHORT position at a 1% significance level, while the LONG portfolio shows a monthly abnormal return of 0.9% at a 5% significance level. When the full 12-month holding period is considered, the SHORT position yields a -0.4% monthly abnormal return at a 5% significance level, while the LONG yields 0.5% monthly abnormal return at a 5% significance level. Considered together, the abnormal return for the PEAD-position is significant at a 1% significance level over all holding periods and yield 2.3%, 1.8% and 0.9% monthly abnormal return respectively. The 0.9% monthly abnormal return over 12-month holding period for the PEAD portfolio is equivalent to the findings by Setterberg (2011) and corresponds to an annualized return of 11.4%. Thus, with RB as estimation for earnings surprise, the results provide strong support for the hypothesis that there is PEAD on the Swedish stock market.

6.1.5. Summary of results across methods

Table 7 presents a summary of the direction of the observed drift and the documented significance levels for the tested holding periods for all methods for estimating the earnings surprise, when the Fama-French factors are considered, i.e., the direction and significance of the intercepts in all previously presented regressions.

Table 7. Summary of PEAD for all holding periods across methods

	SHORT			LONG			PEAD		
	1M	3M	12M	1M	3M	12M	1M	3M	12M
Time-series	- (**)	-	-	-	-	- (*)	+	+	- (*)
Seasonal martingale	-	-	-	-	-	+	-	+	+ (**)
Analyst forecast	- (*)	- (*)	- (*)	+	+	+	+ (**)	+ (**)	+
Event-window return	- (***)	- (***)	- (**)	-	+ (**)	+ (**)	+ (***)	+ (***)	+ (***)

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. +/- indicates the direction of the documented drift. Significance level in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

If we look at the results from the PEAD-position, the overall results support the hypothesis that there is a PEAD on the Swedish stock market, as only the TS results are inconsistent with the other methods. The MG results are weaker but present a drift in the hypothesized direction for two of the holding periods and with a 5% significance level for the 12-month period. AF yields a drift in the hypothesized direction for the PEAD-position over all holding periods of which two at a 5% significance level, which support the claim of a present drift. RB provides strong support, as all holding periods for the PEAD-position yield abnormal return at a 1% significance level. However, as previously mentioned, the characteristic of the drift varies significantly across the choice of earnings surprise estimation method. In general, the results can be summarized to be consistent with previous international research where the different methodologies are compared (Liu et al., 2003). That is, when AF is used as estimation for earnings surprise, the drift tends to be shorter but more prominent than the two historical figures approaches TS and MG, while RB demonstrates the most prominent drift among all four methodologies and for all holding periods at the highest significance levels.

6.2. Stock price synchronicity portfolios

As described in section 5.4., Information noisiness, measured through stock price synchronicity (SPS), is investigated as a driver for PEAD by a division of the full sample into three new portfolios dependent on the level of SPS for individual firms. Thereafter, each earnings surprise portfolio is divided based on the assessed SPS portfolio for each quarter. The new portfolios based on both SPS level and degree of surprise, are used in the regression models specificized in equation 19, 20 and 22. Due to the large number of portfolios and regressions, only the results for the PEAD-position, equation 22, for each methodology is presented in table 8a-d below.

Table 8a. Regression results for PEAD-position with TS divided by high and low SPS

	Low SPS			*High SPS*		
Variables	1M	3M	12M	1M	3M	12M
Intercept	0.017	0.007	-0.001	0.001	-0.006	-0.004
	(0.018)	(0.007)	(0.004)	(0.006)	(0.004)	(0.002)
RMRF	-0.128	-0.059	-0.015	0.316*	-0.109	0.129***
	(0.521)	(0.156)	(0.076)	(0.186)	(0.099)	(0.049)
SMB	-0.056	0.042	0.007	-0.019	-0.023	-0.015
	(0.298)	(0.076)	(0.024)	(0.065)	(0.036)	(0.016)
HML	0.053	-0.013	-0.001	0.023	0.028	0.010**
	(0.176)	(0.050)	(0.007)	(0.037)	(0.022)	(0.005)
N	58	174	696	58	174	696
R^2	0.005	0.004	0.000	0.093	0.020	0.023

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Table 8b. Regression results for PEAD-position with MG divided by high and low SPS

	Low SPS			*High SPS*		
Variables	1M	3M	12M	1M	3M	12M
Intercept	-0.007	-0.003	0.006	-0.004	-0.003	0.003
	(0.008)	(0.0102)	(0.004)	(0.007)	(0.005)	(0.003)
RMRF	0.312	-0.096	0.004	0.149	-0.133	0.028
	(0.233)	(0.252)	(0.088)	(0.184)	(0.109)	(0.054)
SMB	0.227	0.198	0.027	0.189*	0.048	0.014
	(0.139)	(0.140)	(0.032)	(0.110)	(0.037)	(0.019)
HML	-0.176*	-0.113	-0.008	-0.106	-0.045*	-0.001
	(0.091)	(0.109)	(0.007)	(0.066)	(0.026)	(0.005)
N	65	195	780	65	195	780
R^2	0.088	0.013	0.002	0.056	0.027	0.001

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Table 8c. Regression results for PEAD-position with AF divided by high and low SPS

	Low SPS			*High SPS*		
Variables	1M	3M	12M	1M	3M	12M
Intercept	-0.011	-0.008	0.004	0.012	0.000	0.002
	(0.016)	(0.012)	(0.007)	(0.007)	(0.005)	(0.002)
RMRF	0.220	-0.182	0.195	0.261	-0.013	0.108**
	(0.407)	(0.224)	(0.135)	(0.196)	(0.103)	(0.049)
SMB	0.164	0.325**	-0.019	0.095	-0.064	-0.043***
	(0.227)	(0.142)	(0.051)	(0.092)	(0.041)	(0.017)
HML	-0.293	-0.018	0.001	-0.069	0.021	0.010**
	(0.179)	(0.127)	(0.014)	(0.052)	(0.024)	(0.005)
N	60	180	720	60	180	720
R^2	0.078	0.055	0.005	0.083	0.020	0.025

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Table 8d. Regression results for PEAD-position with RB divided by high and low SPS

	Low SPS			*High SPS*		
Variables	1M	3M	12M	1M	3M	12M
Intercept	0.005	0.018***	0.009**	0.028***	0.012**	0.004*
	(0.012)	(0.007)	(0.004)	(0.006)	(0.005)	(0.002)
RMRF	0.005	0.243	-0.002	-0.060	-0.005	0.034
	(0.312)	(0.156)	(0.088)	(0.161)	(0.124)	(0.052)
SMB	-0.430**	-0.047	-0.015	-0.034	-0.045	-0.009
	(0.202)	(0.044)	(0.027)	(0.077)	(0.049)	(0.014)
HML	0.207	-0.030	-0.006	0.022	0.001	0.001
	(0.129)	(0.044)	(0.007)	(0.045)	(0.033)	(0.004)
N	68	204	816	68	204	816
R^2	0.075	0.021	0.001	0.005	0.007	0.001

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

To find evidence of our hypothesis that the level of SPS is a driver of PEAD, we would expect that the subsample with firms with high SPS would present higher or more significant drifts than the subsample of firms with low SPS. The results, presented in table 8a-d, does not provide evidence that SPS has explanatory value for PEAD. Across the methodologies TS, MG and AF the main effect from a division into subsamples based on SPS is that the significance we observed in the regressions on the full sample disappears. For RB, there is still a significant drift for both the high and low SPS samples, nonetheless smaller than for the full sample. The implication of these results could be that the level of SPS is unrelated to PEAD and hence the division of high and low SPS samples creates two subsamples where the possibility to find a drift is disturbed by their smaller sample sizes. Alternatively, a medium level of SPS is a driver of PEAD, but as that would be cumbersome to theorize, it is not further investigated. Rather, it is stated that SPS does not seem to be a driver of PEAD. Hence, there is no evidence for the second hypothesis of this paper.

7. Analysis

The analysis is divided into three subsections. First, we begin with an analysis of the four different earnings surprise measures: TS, MG, AF and RB. Second, we perform robustness tests to evaluate our overall research design. Last, we conduct a final analysis of the results in this study.

7.1. Analysis of the earnings surprise methods

To start of the analysis, we will examine our four approaches for earnings surprise since the choice of methodology seem to have an impact on the overall results in terms of magnitude and duration. It is valuable to identify their differences, similarities, and their ability to predict abnormal future performance to draw broader conclusions of what approach best serves its purpose to predict surprises and subsequently PEAD.

7.1.1. Initial reactions at announcements

A first question is if the methods used to estimate earnings surprises are valid, as they constitute the foundations of our results. To evaluate this, we assume that the market's initial reaction best represents the extent to which the market is surprised by an earnings announcement. Based on this assumption, we investigate the BHAR reaction during the event-window (±1 day around the announcement) on a firm-level, to capture if the initial market reaction corresponds to the surprise according to the estimation methods. We assess the significance through a two-sided t-test. Table 9 present the results from the test for all five portfolios created. It is worth noting that this test is equal to the RB estimation of a surprise, and thus the RB results are of less interest in this context.

Table 9. Initial reaction (BHAR) during event window for the respective methods

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Surprise	Negative	Negative	Uncertain	Positive	Positive
Time-series	-0.014***	-0.005***	0.003	0.015***	0.015***
Seasonal martingale	-0.026***	-0.020***	-0.005***	0.017***	0.020***
Analyst forecasts	-0.019***	-0.008***	0.004*	0.018***	0.028***
Event-window return	-0.106***	-0.033***	-0.000	0.033***	0.122***

*Note: Surprise specifies whether the earnings surprise for the portfolio has been negative, positive or uncertain. The announcement window is specified as ± 1 day, i.e., 3 days and the reaction is the observed BHAR. Significance is assessed through a two-sided t-test. Stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

From table 9 we can draw the conclusion that the estimates do seem to capture the correct surprises. Both the negative surprise portfolios 1 and 2 as well as the positive surprise portfolios 4 and 5 have statistically significant reactions in the hypothesized direction at a 1% significance level across all methods. Further, as excepted, the signs of the reactions differ across methods for portfolio 3 with uncertain surprises, and the significance levels are heterogeneous. We note that the initial reaction with TS is generally smaller than with the other methodologies, which supports the idea that investors do not base expectations on long term historical trend figures. This suggests that TS might not represent the most accurate estimator of earnings surprises, hence the samples in the extreme portfolios might not contain the firms with the greatest surprises and thus not the firms we would expect to drift the most. This line of argument speaks in favor of a drift in the market, as TS presented the weakest evidence for a drift and seem to be the least accurate in identifying the market's perception of a surprise. Nevertheless, none of the methodologies can be completely dismissed based on this analysis as all still present initial abnormal returns in the hypothesized direction.

7.1.2. Ability to predict future performance

As our next step, we investigate how well the methodologies manage to predict which firms will be subject to abnormal returns, under the assumption that there is a relationship between earnings surprises and abnormal return in the market. By quarter on firm-level, the sample is divided into quintiles based on its upcoming 12-month market-based BHAR. The observations are then tabulated in their respective portfolio and their respective BHAR quintile to see if the proportions within each methodology differ significantly. If the methodology has high predictive power, the SHORT (LONG) portfolio should be overrepresented by observations found in low (high) BHAR quintiles. Table 10 presents the percentage of predicted observations across the methodologies.

Table 10. Performance (BHAR) quintile distribution in the SHORT and LONG portfolio

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Time-series					
SHORT	19%	22%	21%	20%	19%
LONG	17%	22%	23%	20%	17%
Seasonal martingale					
SHORT	25%	22%	18%	16%	20%
LONG	23%	19%	18%	18%	22%
Analyst forecast					
SHORT	18%	23%	21%	20%	19%
LONG	12%	20%	25%	23%	20%
Event-window return					
SHORT	29%	21%	17%	15%	18%
LONG	18%	18%	19%	21%	25%

Note: The table presents the distribution of observations in each LONG and SHORT portfolio in respect to their BHAR development under the succeeding 12 months when split into quintiles.

In table 10, we can see that the most accurate predictions among the methodologies are found in RB which is expected as those portfolios yield the most prominent drifts. Further, the results confirm that the TS portfolios do not capture the future performance of stocks and it is noteworthy that the LONG portfolio is skewed towards the lower two quintiles. In general, the methodologies are slightly more predictive in the SHORT portfolio than the LONG, apart from AF. To evaluate the significance of these results, one can assess the likelihood of such division if it was done randomly with equal probabilities. If so, binominal probabilities can be used to calculate the likelihood of an appearance of these results by chance. We use a setting where the

LONG (SHORT) portfolio has performed a correct estimation if the firm-quarter observation is within quintile 4 or 5 (1 or 2). The probability to, by chance, correctly predict each observation by chance would thus be 40%. Based on this setting, the likelihood of the observed (or more accurate) distribution of prediction is calculated with the binominal distribution function and the results are presented in appendix 4. For RB, with its 3487 and 3030 observations in the SHORT and LONG portfolio respectively, the probability to see such skewed division by chance is considerably below 1‰ for both portfolios. Similar result is seen for the SHORT position in MG, while the skewness towards quintile 4 or 5 in the LONG portfolio can be expected in 57% of cases where one thus not with any significant certainty can confirm that MG has predictability. In AF, the skewness in the LONG position has a probability of 1% while the skewness in the SHORT position can be expected 26% of the times by chance. Lastly, TS SHORT portfolio will with 44% chance reach the skewness in the SHORT portfolio, while chance would be as successful at predict which firms that will be in quintiles 4 and 5 as the LONG portfolio in 97% of its attempts. However, we can note that there is an overrepresentation of firms in quintile 3 in the LONG TS portfolio, which yields that there is no significance in its ability to predict firms in quintile 1 or 2 either (81% probability that chance would have the same accuracy). From these results, we can further emphasize the strength of the RB results in this paper, while one should be more cautious around the other methodologies as their predictability may be an effect of chance. The last holds especially for TS.

7.2. Robustness of research design

To investigate if the results presented are an effect of the overall chosen research design, we conduct several robustness tests to assess the strength of the results. For these, result tables for RB are presented in the main text, as this method is where a drift is most clearly found and for which the results are of most interest to ensure robustness. However, all results of the robustness tests for the other methodologies can be found in the appendix and notable results from them are commented in the analysis.

7.2.1. Extended event-window and postponement of portfolio formation

As a first robustness test, we extent the event-window to include the first five days after the announcement and thus the portfolio formation takes place 4 trading days later than in the original research design. This is mainly related to the assumption of how fast the market response to an announcement needs to be, to be considered immediate. The window is extended to ensure that the drift is not driven by market activity during a period which could be argued to be seen as immediate. The regression results for RB are presented below in table 11 and the corresponding regression results for TS, MG and AF are presented in appendix 5.

Table 11. Regression results with 5 days event-window with RB

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.018***	-0.008**	-0.003*	0.004	0.008**	0.004**	0.022***	0.016***	0.007***
	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.005)	(0.004)	(0.002)
RMRF	1.175***	0.950***	0.984***	0.947***	1.078***	1.006***	-0.227	0.128	0.021
	(0.135)	(0.070)	(0.042)	(0.139)	(0.074)	(0.038)	(0.148)	(0.091)	(0.052)
SMB	0.238***	0.076***	0.034***	-0.013	0.012	0.046***	-0.251**	-0.065*	0.013
	(0.077)	(0.029)	(0.012)	(0.080)	(0.031)	(0.011)	(0.085)	(0.038)	(0.015)
HML	-0.164**	-0.008	0.001	-0.024	-0.021	-0.001	0.140**	-0.013	-0.001
	(0.054)	(0.025)	(0.003)	(0.056)	(0.027)	(0.003)	(0.060)	(0.033)	(0.004)
N	68	204	816	68	204	816	68	204	816
R^2	0.554	0.496	0.406	0.426	0.517	0.470	0.138	0.030	0.001

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Generally, the results are robust to the extension of the event-window for RB. The PEAD-position sees an abnormal return in the hypothesized direction over all holding periods on a 1% significance level, although the amplitude has decreased slightly (approximately 0.2 p.p. of monthly abnormal return). This tendency of lost amplitude remains throughout the holding periods in the LONG and SHORT positions as well, where the diminished significance is further evident for the two extended durations in the SHORT position. The deviant development is seen in the 1-month holding period in the LONG portfolio where the original results yielded a -0.1% abnormal return and in this test the portfolio yields a 0.4% abnormal return. Both results are without significance, but the difference points toward that the abnormal return in opposite direction to the hypothesized direction, seen in the short holding period in the LONG portfolio, is driven by a reversal in the days immediately after the original event-window. This implies an immediate overreaction to positive earnings surprises, in line with the findings of Milian (2015). However, this development is not seen in the SHORT position, where the 1-month abnormal return is smaller for the extended event-window and the same holds for the other methodologies, hence it should be interpreted with caution. Nevertheless, the results appear to be robust to an extension of the event-window across all methodologies and difference in results reminiscent those of RB.

7.2.2. Regressions based on common sample

As pointed out earlier in the paper, the samples differ in size across the methodologies due to the different requirements needed to create the earnings estimates. To be included in the smallest sample, AF, the firm must be followed by financial analysts who publish their forecasts in the I/B/E/S database and to be included in the TS sample, the firm needs to have complete earnings history for the preceding nine quarters. To ensure that the discovered drifts and the differences in drifts across methods are not mainly due to a selection bias we perform the regressions on a common sample where we include only the observations included in all methods. This common sample consists of a total of 5,031 firm-quarter observations, which can be compared to the total AF sample of 5,175 which implies that AF limits the sample the most. However, the number of quarters included is mainly limited by TS, as there are quarters in the early years of the dataset that are not included in the TS sample due to its estimation process. This sheds light on the skewness in the sample of AF where the early quarters consist of a small number of observations compared to the latter, as relatively few firm-quarter observations disappear due to the limitation of TS. The results for RB are presented below in table 12 and the corresponding results for TS, MG and AF are presented in appendix 6.

Table 12. Regression results with RB based on common sample

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.014***	-0.008**	0.000	0.004	0.004	0.002	0.018***	0.012***	0.002
	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
RMRF	0.889***	1.078***	0.938***	1.133***	1.132***	1.188***	0.244*	0.054	0.250***
	(0.129)	(0.076)	(0.042)	(0.132)	(0.065)	(0.054)	(0.127)	(0.088)	(0.062)
SMB	0.045	-0.012	0.012	0.043	0.008	0.022	-0.002	0.020	0.010
	(0.042)	(0.027)	(0.014)	(0.043)	(0.023)	(0.018)	(0.042)	(0.031)	(0.021)
HML	-0.028	0.008	0.003	-0.027	-0.003	0.004	0.002	-0.011	0.000
	(0.024)	(0.016)	(0.004)	(0.025)	(0.014)	(0.005)	(0.024)	(0.019)	(0.006)
N	58	174	696	58	174	696	58	174	696
R^2	0.526	0.592	0.475	0.629	0.688	0.464	0.078	0.005	0.028

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

When the regressions are performed on the matching sample throughout the methods, it can be noted that the results for RB to a larger extent reminiscent the original results of AF with a drift that is more prominent over the shorter holding periods, and mainly driven by the SHORT position. This tendency confirms the characteristics of the drift for the subsample of analyst followed firms, which appear to differ from the full sample drift. Further, it echoes previous studies, where drifts based on AF generally are shorter as the firms are larger (which can be seen in appendix 6c) and more intensively followed which creates a more efficient trade in their shares (see for example Ayers et al., 2011; Milian, 2015). In turn, we conclude that the drift in the longer holding periods, seen in both MG and RB, is generally driven by firms that is does not have analyst following. It is noteworthy that RB still yields a larger and more significant drift than AF which adds robustness to its ability to capture earnings surprises across subsamples. The prominent drift in the SHORT position differs from previous results in the Swedish setting but has previously been rationalized in other smaller capital markets by the fact that it is generally more cumbersome to take a short position to exploit a mispricing (Booth et al., 2011). Altogether, the results add robustness to the previous results of AF, yet the results highlight the need to assess the characteristics of the sample if one was to exploit the anomaly in practice.

7.2.3. Regressions based on 10 portfolios

In the majority of previous studies of PEAD, the samples are divided into ten portfolios rather than the five used in this paper. The rationale behind this, as mentioned, is to ensure that there is a reasonable number of observations within the extreme portfolios, especially when divided based on SPS since the Swedish market is smaller than the most studied markets of the US or the UK. To ensure that the results are not substantially skewed by this decision, we perform the same regressions on the extreme portfolios from a division into 10 portfolios across methodologies. The result tables for RB is presented below in table 13 and the results for TS, MG and AF are presented in appendix 2. The results show that RB and MG drift is robust to this alteration, where the significance is the same but the amplitude slightly larger (now 1.1 and 1.0% monthly abnormal return over 12-month holding period, respectively for RB and MG). For TS and AF, the significant drifts have disappeared. For AF, the amplitude is intact although the standard error has increased which yields an unsignificant drift. This may be explained by the methodology's smaller sample which amplify the effect from a division into 10 portfolios. Nevertheless, this test further show that the most robust results are those of RB.

Table 13. Regression results with RB based on 10 portfolios

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.024***	-0.008*	-0.005**	-0.002	0.006	0.005*	0.022**	0.014**	0.011***
	(0.006)	(0.004)	(0.003)	(0.010)	(0.004)	(0.003)	(0.011)	(0.006)	(0.004)
RMRF	1.138***	0.669***	0.879***	0.481	0.929***	0.959***	-0.658*	0.261*	0.079
	(0.194)	(0.105)	(0.055)	(0.302)	(0.097)	(0.060)	(0.334)	(0.138)	(0.080)
SMB	0.237**	0.063	0.052***	0.105	0.004	0.081***	-0.132	-0.059	0.029
	(0.094)	(0.047)	(0.015)	(0.146)	(0.044)	(0.016)	(0.162)	(0.062)	(0.021)
HML	-0.144**	-0.015	0.002	-0.059	-0.002	-0.005	0.084	0.012	-0.007
	(0.056)	(0.032)	(0.005)	(0.088)	(0.029)	(0.005)	(0.097)	(0.042)	(0.001)
N	68	204	816	68	204	816	68	204	816
R^2	0.384	0.176	0.254	0.045	0.319	0.263	0.065	0.025	0.004

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

7.3. Implementable trading strategy

As a final test, we investigate whether the drift exists when one considers the main drawback of event-time methodology: the difficulty to build an implementable trading strategy as one need to know what positions to take ex-ante. For test this, we use the calendar-time trading strategy to see if a drift can be exploited with this setting. The portfolio positions are now taken on the first trading day in the subsequent quarter in relation to the announcement day, instead of two trading days after the announcement. For example, if the announcement day for first quarter results is April 24th and the surprise yields a position in the LONG (SHORT) portfolio, the firm share is bought (sold) on July 1st. In turn, there could in theory be up to a three-month lag between first and last announcement, and most as of the observations announce earnings during the first month in the quarter it creates a long average period between announcement and portfolio formation. As with the robustness tests, the focus is on the RB as that is where the most robust drift is found and from which a trading strategy could possibly be created. The results are presented in table 14 and the results for the other methodologies can be found in appendix 7.

Table 14. Calendar-time regression results with RB as estimation for earnings surprise

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.023***	-0.012**	-0.003	0.004	0.012	0.008**	0.028*	0.024***	0.011**
	(0.007)	(0.005)	(0.003)	(0.014)	(0.008)	(0.004)	(0.014)	(0.007)	(0.005)
RMRF	0.897***	0.915***	0.757***	1.349***	1.105***	0.956***	0.303	0.144	0.089
	(0.147)	(0.096)	(0.069)	(0.316)	(0.128)	(0.076)	(0.312)	(0.148)	(0.097)
SMB	0.136	0.050**	0.073***	0.396	0.078***	0.078***	0.187	0.026	0.003
	(0.126)	(0.020)	(0.022)	(0.276)	(0.027)	(0.025)	(0.269)	(0.031)	(0.031)
HML	0.194	0.118	-0.009	-0.283	-0.091	-0.0134	-0.396	-0.229	-0.004
	(0.191)	(0.105)	(0.008)	(0.417)	(0.144)	(0.008)	(0.406)	(0.162)	(0.011)
N	68	204	816	68	204	816	68	204	816
R^2	0.709	0.525	0.174	0.410	0.424	0.208	0.022	0.016	0.002

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

The results in table 14 show that there would be possible to execute a trading strategy based on the PEAD-position with the RB portfolios. For a the 3-month holding period, the strategy would generate a monthly abnormal return of 2.4% at a 1% significance level, which corresponds to a total abnormal return of 7.4% over three months. Over the 12-month holding period, the strategy would yield a 1.1% monthly abnormal return at a 5% significance level, equal to an annualized abnormal return of 14.0%. Over the same holding period with equal significance, one could take the LONG position and earn 0.8% monthly abnormal return, equal to an annualized abnormal return of 10.0%. This strategy could be implemented by a retail investor and these results thus point to the conclusion that there is a market anomaly present.

7.4. Analysis of final results

In total, the results of this paper suggest a present PEAD in the Swedish market and the results seem to be robust to research design choices. In addition, it is not solely a theoretical abnormal return that is observed, but the results suggest that a trading strategy could be implemented by an investor to monetize the anomaly. The characteristic of the drift is found to vary across earnings estimation methods, which may be assigned to the differences in the samples, since the results varied when the regressions were performed on a common sample. The common sample reminiscent that of AF, as that is the most limiting sample, which is characterized by larger firms (as seen in appendix 8). As the drift seem to be generally shorter with AF and over the common sample, it points to a tendency that the drift over longer holding periods is driven by smaller firms. Such tendency was found by Setterberg (2011) and was mentioned already by Bernard & Thomas (1989), so it does not serve as a revolutionary finding. However, it highlights that one should be cautious with statements of how the drift has evolved over time since the last Swedish study, as the samples differ. In the study of Setterberg (2011), the mean market value was approximately 34 billion SEK, compared with 10 billion SEK for the full sample in this paper (and 21 billion SEK for the AF subsample), which is remarkable given the difference in periods.

Additionally, in this paper the only risk controls included in the regressions are the Fama-French three-factor model which may have implication for the results. To further test the robustness of the results one could have tested with other control variables such as the traditional CAPM model, or with the additional two factors proposed to the Fama-French three-factor model in terms of momentum (Carhart, 1997) and the newer adjustment of accounting for profitability and investment patterns (Fama & French, 2015). Or other alternative measures of risks that have been proposed in the PEAD literature such as leverage, R&D expenses, cash flow effects and capital expenditures (Dargenidou et al., 2018) which could potentially have served as proxies for risk.

Further, it is noteworthy that the drift is found to be slightly different in the short and long position, where the general tendency is that the short positions see a drift over the shorter holding periods while the long positions see a drift over the longer periods. This may implicate that there is a common omitted risk factor that is priced in and creates higher expected return for both the long and short position and gradually becomes more important. One such factor could be the 'information risk factor', discussed by Francis et al. (2007) as one of two forces within the information uncertainty that could explain differences in how the long and short position develop over time.[4] The information risk factor relates to the risk of surprises, as all firms in the extreme surprise portfolios have history of delivering either positive or negative surprises, which represents uncertainty that investors want to get paid for. Hence, it would create an upward drift in both positions.

As for the second part of the research question, whether information noisiness has explanatory value to PEAD, we find no tendency of such relationship. At least not when SPS is used as the measure for information noisiness. In our research design, it was aimed to avoid hindsight bias and thus a backward-looking calculation of SPS was conducted. This relies on the assumption that firms with high noisiness prior to earnings announcements are the ones whose return following an announcement can be explained by market and industry returns. This may be a valid assumption, but it is possible that there are considerable differences in the two periods which would make it more valid to investigate the SPS levels across firms after the

[4] The other part in their information uncertainty framework is the learning effect, which rather is an explainer of the drift itself, as it hypothesizes that it takes time for investors to understand the implications of the surprise (a disbelief in the EMH). Not related to the differences in characteristics of the drift in the short and long position.

announcement, as that is when the drift occurs. However, this would impede the ability to ex-ante say what firms that will drive the PEAD, yet it could still potentially characterize firms with a tendency of a prolonged reaction ex-post. Another potential explanation to the weak results of SPS is that there is reasonable to believe that there are subsamples within the full sample that have diverging ‘base-levels’ of SPS as the sample consists of a broad variety of firms. One such factor that could have impacted the measure is liquidity, as illiquid stocks show volatile returns from a low level of trades which would yield a low SPS, which thus disturb the metric. The effect of such factors may not correspond with the drivers of PEAD, but rather be a flaw of SPS that is more considerable at a smaller capital market such as the Swedish.

8. Conclusion and suggestions for future research

This paper has examined the existence of post-earnings announcement drift on the Swedish stock market, using 4 different estimation methods to the concept of earnings surprises. Further, it has investigated whether the concept of information noise through stock price synchronicity presents an explanatory driver of the drift. The main findings of the paper are aligned with our first hypothesis that there is evidence of PEAD on the Swedish market, but the magnitude and length of this drift varies depending on the chosen approach of estimating what is an earnings surprise. When analyst forecasts are used as the basis for surprises, the drift is shorter and only significant over 3 months, with a monthly abnormal return of 0.7% at a 5% significance level. While as for the seasonal martingale approach, a monthly abnormal return of 0.7% is observed for the 12-month holding period at a 5% significance level but not for the shorter holding periods. With the event-window return approach, the drift is significant for all tested holding periods, with a monthly abnormal return of 0.9% for a 12-month holding period at a 1% significance level. The results are robust for changes in the research design and when tested with the calendar-time method, a more practice-oriented approach which can be implemented by investors, the results remain significant. With the RB approach, an investor can generate a monthly abnormal return of 2.4% at a 1% significance level for the 3-month holding period, which corresponds to a total abnormal return of 7.4%. Over the 12-month holding period, the strategy would yield an annualized return of 14.0% at a 5% significance level. Thus, the results of this paper provide evidence of inefficiency in the Swedish stock market, which echoes the findings of Setterberg (2011). As for the second hypothesis of the paper, and the attempt to explain the existence of the drift with the variable of stock price synchronicity, no significant results are obtained for any of the four methods, and the robustness of the design have not been further tested due to the non-existence of initial results.

The results of the paper generate further questions within the research area of PEAD and inspiration for future research. First, it would be of interest to perform a similar comparison of all these four methodologies for estimating earnings surprises on a market that allows for a bigger sample over a greater period, to see if the variance in the results holds also for bigger capital markets. Second, this paper did not test PEAD with the more theoretically correct measure of cumulative abnormal return, CAR. Hence, it would be of interest to see if the results in this paper, as well as the results from Setterberg (2011) for the Swedish market still holds if

CAR is used as the main measure of return. Lastly, this paper has not in dept tried to explain the relationship between the different earnings estimation methodologies, such as to what extent they subsume each other or can be considered independent. As the characteristic of the drift appear to differentiate across methodologies, this would be an interesting add-on to our findings, for example by following Liu et al. (2003). As for the second hypothesis of this paper, information noisiness was only approximated through the measure of stock price synchronicity. In the literature, there are other suggested approximations for information noise, such as firms' analyst coverage, analyst forecast divergence and trading volumes which could all serve as possible proxies for firm noise in a more thorough investigation of the potential relationship between PEAD and information noisiness.

References

Abarbanell, J. S., & Bushee, B. J. (1998). Abnormal Returns to a Fundamental Analysis Strategy. *The Accounting Review, 73*(1), 19-45.

Ariff, M., Loh, A. L. C., & Chew, P. M. K. (1997). The Impact of Accounting Earnings Disclosures on Stock Prices in Singapore. *Asia Pacific Journal of Management, 14*(1), 17. 10.1023/A:1015429012076

Ayers, B. C., Li, O. Z., & Yeung, P. E. (2011). Investor Trading and the Post-Earnings-Announcement Drift. *The Accounting Review, 86*(2), 385-416. 10.2308/accr.00000027

Ball, R., & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research, 6*(2), 159-178. 10.2307/2490232

Barber, B. M., & Lyon, J. D. (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics, 43*(3), 341-372. 10.1016/S0304-405X(96)00890-2

Bartov, E. L. I., Lindahl, F. W., & Ricks, W. E. (1998). Stock price behavior around announcements of write-offs. *Review of Accounting Studies*, *3*(4), 327-346. 10.1023/A:1009644800963

Beaver, W. H. (1981). Market Efficiency. *The Accounting Review, 56*(1), 23-37.

Berk, J. B., & DeMarzo, P. M. (2017). *Corporate finance* (4th ed.). Pearson.

Bernard, V. L., & Thomas, J. K. (1989). Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? *Journal of Accounting Research*, *27*(2), 1-36. 10.2307/2491062

Bernard, V. L., & Thomas, J. K. (1990). *Evidence that stock prices do not fully reflect the implications of current earnings for future earnings*. Elsevier BV. 10.1016/0165-4101(90)90008-r

Booth, G., Kallunki, J., Sahlström, P., & Tyynelä, J. (2011). Foreign vs domestic investors and the post-announcement drift. *International Journal of Managerial Finance, 7*(3), 220-237. 10.1108/17439131111144441

Brown, L. D., Hagerman, R. L., Griffin, P. A., & Zmijewski, M. E. (1987). Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings. *Journal of Accounting & Economics, 9*(1), 61-87. 10.1016/0165-4101(87)90017-6

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance (New York), 52*(1), 57-82. 10.1111/j.1540-6261.1997.tb03808.x

Chen, C., & Doukas, J. A. (2020). *Stock price synchronicity, cognitive biases, and momentum*. Wiley. 10.1111/eufm.12294

Chordia, T., & Shivakumar, L. (2005). Inflation Illusion and Post-Earnings-Announcement Drift. *Journal of Accounting Research, 43*(4), 521-556. 10.1111/j.1475-679X.2005.00181.x

Chordia, T., Subrahmanyam, A., & Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? *Journal of Accounting and Economics, 58*(1), 41-58. 10.1016/j.jacceco.2014.06.001

Chudek, M., Truong, C., & Veeraraghavan, M. (2011). Is trading on earnings surprises a profitable strategy? Canadian evidence. *Journal of International Financial Markets, Institutions & Money, 21*(5), 832-850. 10.1016/j.intfin.2011.06.004

Clement, M., Lee, J., & Yong, K. O. (2019). A new perspective on post-earnings-announcement-drift: Using a relative drift measure. *Journal of Business Finance & Accounting, 46*(9-10), 1123-1143. 10.1111/jbfa.12401

Dargenidou, C., Tonks, I., & Tsoligkas, F. (2018). Insider trading and the post-earnings announcement drift. *Journal of Business Finance & Accounting, 45*(3-4), 482-508. 10.1111/jbfa.12305

De Bondt, W. F. M., & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance (New York), 40*(3), 793-805. 10.1111/j.1540-6261.1985.tb05004.x

Dong, Y., Li, O. Z., Lin, Y., & Ni, C. (2016). Does Information-Processing Cost Affect Firm-Specific Information Acquisition? Evidence from XBRL Adoption. *Journal of Financial and Quantitative Analysis; J.Financ.Quant.Anal, 51*(2), 435-462. 10.1017/S0022109016000235

Doyle, J. T., Lundholm, R. J., & Soliman, M. T. (2006). The extreme future stock returns following I/B/E/S earnings surprise. *Journal of Accounting Research, 44*(5), 849.

Durnev, A., Morck, R., & Yeung, B. (2004). Value-Enhancing Capital Budgeting and Firm-specific Stock Return Variation. *Journal of Finance, 59*(1), 65-105. 10.1111/j.1540-6261.2004.00627.x

Durnev, A., Morck, R., Yeung, B., & Zarowin, P. (2003). Does Greater Firm-Specific Return Variation Mean More or Less Informed Stock Pricing? *Journal of Accounting Research, 41*(5), 797-836. 10.1046/j.1475-679X.2003.00124.x

Ertimur, Y., Livnat, J., & Martikainen, M. (2003). Differential Market Reactions to Revenue and Expense Surprises. *Review of Accounting Studies, 8*(2-3), 185. 10.1023/a:1024409311267

Fama, E. F. (1965). Random Walks in Stock Market Prices. *Financial Analysts Journal, 21*(5), 55-59. 10.2469/faj.v21.n5.55

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical work. *The Journal of Finance (New York), 25*(2), 383-417. 10.1111/j.1540-6261.1970.tb00518.x

Fama, E. F. (1976). Efficient Capital Markets: Reply. *The Journal of Finance (New York), 31*(1), 143-145. 10.2307/2326404

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics, 49*(3), 283-306. 10.1016/S0304-405X(98)00026-9

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56. 10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (2004). The Capital Asset Pricing Model: Theory and Evidence. *The Journal of Economic Perspectives, 18*(3), 25-46. 10.1257/0895330042162430

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1-22. 10.1016/j.jfineco.2014.10.010

Forner, C., & Sanabria, S. (2010). Post-Earnings Announcement Drift in Spain and Behavioural Finance Models. *The European Accounting Review, 19*(4), 775-815. 10.1080/09638180903503978

Foster, G. (1979). Briloff and the Capital Market. *Journal of Accounting Research, 17*(1), 262-274. 10.2307/2490317

Foster, G., Olsen, C., & Shevlin, T. (1984). Earnings Releases, Anomalies, and the Behavior of Security Returns. *The Accounting Review, 59*(4), 574-603.

Francis, J., LaFond, R., Olsson, P., & Schipper, K. (2005). The market pricing of accruals quality. *Journal of Accounting & Economics, 39*(2), 295-327. 10.1016/j.jacceco.2004.06.003

Francis, J., Lafond, R., Olsson, P., & Schipper, K. (2007). Information Uncertainty and Post-Earnings-Announcement-Drift. *Journal of Business Finance & Accounting, 34*(3-4), 403-433. 10.1111/j.1468-5957.2007.02030.x

Francis, J., & Schipper, K. (1999). Have Financial Statements Lost Their Relevance? *Journal of Accounting Research, 37*(2), 319-352. 10.2307/2491412

Fricke, E., Fung, S., & Goktan, M. S. (2014). Google search, information uncertainty, and post-earnings announcement drift. *Journal of Accounting and Finance, 14*(2), 11.

Gerard, X. (2012). Information Uncertainty and the Post—Earnings Announcement Drift in Europe. *Financial Analysts Journal, 68*(2), 51-69. 10.2469/faj.v68.n2.4

Greig, A. C. (1992). Fundamental analysis and subsequent stock returns. *Journal of Accounting & Economics, 15*(2), 413-442. 10.1016/0165-4101(92)90026-X

Griffin, J. M., Kelly, P. J., & Nardari, F. (2010). Do Market Efficiency Measures Yield Correct Inferences? A Comparison of Developed and Emerging Markets. *The Review of Financial Studies, 23*(8), 3225-3277. 10.1093/rfs/hhq044

Haugen, R. A. (2002). *The Inefficient Stock Market: What Pays Off and Why* (2nd ed.). Prentice-Hall.

Holthausen, R. W., & Watts, R. L. (2001). The relevance of the value-relevance literature for financial accounting standard setting. *Journal of Accounting & Economics, 31*(1), 3-75. 10.1016/S0165-4101(01)00029-5

Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque financial reports, R2, and crash risk. *Journal of Financial Economics, 94*(1), 67-86. 10.1016/j.jfineco.2008.10.003

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of Financial Economics, 6*(2), 95-101. 10.1016/0304-405X(78)90025-9

Karlsson, H., & Jeganmohan, M. (2020). *Accelerate your returns? An examination of Earnings Acceleration and a range of other earnings-related stock market anomalies - The Swedish Case*. Handelshögskolan i Stockholm.

Kishore, R., Brandt, M. W., Santa-Clara, P., & Venkatachalam, M. (2008). Earnings Announcements are Full of Surprises. *SSRN Electronic Journal,* 10.2139/ssrn.909563

Lee, Y. (2012). The Effect of Quarterly Report Readability on Information Efficiency of Stock Prices. *Contemporary Accounting Research, 29*(4), 1137-1170. 10.1111/j.1911-3846.2011.01152.x

Li, Y., Nekrasov, A., & Teoh, S. H. (2020). Opportunity knocks but once: delayed disclosure of financial items in earnings announcements and neglect of earnings news. *Review of Accounting Studies, 25*(1), 159-200. 10.1007/s11142-019-09519-7

Liang, L. (2003). Post-Earnings Announcement Drift and Market Participants' Information Processing Biases. *Review of Accounting Studies, 8*(2-3), 321. 10.1023/A:1024477831740

Liu, W., Strong, N., & Xu, X. (2003). Post-earnings-announcement Drift in the UK. *European Financial Management : The Journal of the European Financial Management Association, 9*(1), 89-116. 10.1111/1468-036X.00209

Livnat, J., & Mendenhall, R. R. (2006). Comparing the Post-Earnings Announcement Drift for Surprises Calculated from Analyst and Time Series Forecasts. *Journal of Accounting Research, 44*(1), 177-205. 10.1111/j.1475-679X.2006.00196.x

Lo, A. W., & MacKinlay, A. C. (2002). *A non-random walk down Wall Street*. Princeton University Press.

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature, 35*(1), 13-39.

Malkiel, B. G. (2003). The Efficient Market Hypothesis and Its Critics. *The Journal of Economic Perspectives, 17*(1), 59-82. 10.1257/089533003321164958

Milian, J. A. (2015). Unsophisticated Arbitrageurs and Market Efficiency: Overreacting to a History of Underreaction? *Journal of Accounting Research, 53*(1), 175-220. 10.1111/1475-679X.12070

Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics, 58*(1), 215-260. 10.1016/S0304-405X(00)00071-4

Narayanamoorthy, G. (2006). Conservatism and Cross-Sectional Variation in the Post-Earnings Announcement Drift. *Journal of Accounting Research, 44*(4), 763-789. 10.1111/j.1475-679X.2006.00218.x

Ou, J. A., & Penman, S. H. (1989). Financial statement analysis and the prediction of stock returns. *Journal of Accounting & Economics, 11*(4), 295-329. 10.1016/0165-4101(89)90017-7

Richardson, S., Tuna, İ, & Wysocki, P. (2010). Accounting anomalies and fundamental analysis: A review of recent research advances. *Journal of Accounting and Economics, 50*(2), 410-454. 10.1016/j.jacceco.2010.09.008

Roll, R. (1988). R2. *The Journal of Finance (New York), 43*(3)10.1111/j.1540-6261.1988.tb04591.x

Sen, K. (2009). Earnings surprise and sophisticated investor preferences in India. *Journal of Contemporary Accounting & Economics, 5*(1), 1-19. 10.1016/j.jcae.2008.11.001

Setterberg, H. (2011). *The pricing of earnings : essays on the post-earnings announcement drift and earnings quality risk*

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance (New York), 19*(3), 425. 10.2307/2977928

Skogsvik, S., & Skogsvik, K. (2010). Accounting-Based Probabilistic Prediction of ROE, the Residual Income Valuation Model and the Assessment of Mispricing in the Swedish Stock Market. *Abacus (Sydney), 46*(4), 387-418. 10.1111/j.1467-6281.2010.00325.x

Truong, C. (2011). Post-earnings announcement abnormal return in the Chinese equity market. *Journal of International Financial Markets, Institutions & Money, 21*(5), 637-661. 10.1016/j.intfin.2011.04.002

van Huffel, G., Joos, P., & Ooghe, H. (1996). Semi-annual earnings announcements and market reaction: some recent findings for a small capital market. *The European Accounting Review, 5*(4), 693-713. 10.1080/09638189600000043

Wang, X. W., Yan, Z., Zhang, Q., & Gao, X. (2018). Investor attention and stock market under-reaction to earnings announcements: Evidence from the options market. *The Journal of Futures Markets, 38*(4), 478-492. 10.1002/fut.21890

Zhang, S., & Gregoriou, A. (2020). Post earnings announcement drift, liquidity and zero leverage firms: Evidence from the UK stock market. *Journal of Business Research, 116*, 13-26. 10.1016/j.jbusres.2020.05.005

Sverige Riksbank (2016). *The Swedish Financial Market 2016.* ISSN 2001-5046, Stockholm 2016 Available at: https://www.riksbank.se/globalassets/media/rapporter/den-svenska-finansmarknaden/svenska/2016/rap_finansm_160831_sve.pdf

Appendices

Appendix 1a. Descriptive statistics of portfolio 1 and 5 with time-series estimation

	Portfolio 1					Portfolio 5				
Variables	N	Mean	Std	Min	Max	N	Mean	Std	Min	Max
Reported EPS	2,164	-0.474	2.610	-34.37	5.937	1,423	1.427	2.323	-17.87	16.46
Expected EPS	2,164	1.135	2.045	-10.49	24.72	1,423	-0.991	3.736	-34.95	7.679
Unexpected EPS	2,164	-1.609	3.019	-44.79	0.0360	1,423	2.419	3.202	0.0736	36.30
SUE	2,164	-2.240	1.874	-40.93	0.0167	1,423	1.570	0.890	0.476	7.180

Note: Reported EPS is the reported earnings per share in the announcement. Expected EPS is the expected earnings estimated with the respective estimation method. Unexpected EPS is the difference between the reported EPS and the expected EPS. SUE is the standardized unexpected earnings calculated as the unexpected earnings divided by the closing stock price of the previous quarter.

Appendix 1b. Descriptive statistics of portfolio 1 and 5 with seasonal martingale

	Portfolio 1					Portfolio 5				
Variables	N	Mean	Std	Min	Max	N	Mean	Std	Min	Max
Reported EPS	2,366	-1.024	3.489	-45.74	8.135	3,124	0.597	1.954	-18.36	14.14
Expected EPS	2,326	0.788	2.620	-23.40	40.74	3,092	-1.064	3.994	-49.26	10.02
Unexpected EPS	2,326	-1.837	3.519	-49.59	0.756	3,092	1.675	3.702	0.0020	49.61
SUE	2,323	-0.144	0.572	-15.49	0.127	3,092	0.163	0.738	0.0079	28.43

Note: Reported EPS is the reported earnings per share in the announcement. Expected EPS is the expected earnings estimated with the respective estimation method. Unexpected EPS is the difference between the reported EPS and the expected EPS. SUE is the standardized unexpected earnings calculated as the unexpected earnings divided by the closing stock price of the previous quarter.

Appendix 1c. Descriptive statistics of portfolio 1 and 5 with analyst forecast

	Portfolio 1					Portfolio 5				
Variables	N	Mean	Std	Min	Max	N	Mean	Std	Min	Max
Reported EPS	1,636	-1.474	4.238	-51.58	13.42	1,408	2.131	3.048	-1.40	16.66
Expected EPS	1,636	1.147	1.921	-13.98	16.78	1,408	0.357	1.226	-1.98	6.00
Unexpected EPS	1,636	-2.823	4.036	-44.19	-0.03	1,408	1.774	2.189	0.02	16.98
SUE	1,636	-0.154	0.449	-8.26	-0.01	1,408	0.101	0.497	0.01	11.50

Note: Reported EPS is the reported earnings per share in the announcement. Expected EPS is the expected earnings estimated with the respective estimation method. Unexpected EPS is the difference between the reported EPS and the expected EPS. SUE is the standardized unexpected earnings calculated as the unexpected earnings divided by the closing stock price of the previous quarter.

Appendix 1d. Descriptive statistics of portfolio 1 and 5 with event-window return

	Portfolio 1					Portfolio 5				
Variables	N	Mean	Std	Min	Max	N	Mean	Std	Min	Max
Reported EPS	3,487	-0.869	4.997	-51.58	15.38	3,030	0.302	3.313	-52.01	16.73
AAWR	3,487	-0.106	0.060	-0.604	-0.009	3,030	0.122	0.158	0.035	6.523

Note: Reported EPS is the reported earnings per share in the announcement. AAWR is the abnormal BHAR during the announcement window.

Appendix 2a. Regression results with TS based on 10 portfolios

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.015**	-0.001	-0.002	-0.007	-0.006	-0.007**	0.008	-0.005	-0.004
	(0.006)	(0.004)	(0.002)	(0.006)	(0.004)	(0.003)	(0.008)	(0.004)	(0.004)
RMRF	0.847***	0.790***	0.761***	0.920***	0.750***	0.961***	0.073	-0.040	0.200**
	(0.184)	(0.091)	(0.047)	(0.187)	(0.094)	(0.071)	(0.245)	(0.106)	(0.081)
SMB	0.139**	-0.036	0.020	0.069	-0.018	0.016	-0.071	0.018	-0.004
	(0.069)	(0.028)	(0.015)	(0.070)	(0.028)	(0.023)	(0.092)	(0.032)	(0.027)
HML	-0.085**	0.022	0.002	-0.029	0.036**	0.009	0.057	0.013	0.007
	(0.040)	(0.018)	(0.004)	(0.040)	(0.018)	(0.006)	(0.053)	(0.020)	(0.007)
N	58	174	696	58	174	696	58	174	696
R^2	0.360	0.351	0.311	0.365	0.327	0.247	0.036	0.011	0.013

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Appendix 2b. Regression results with MG based on 10 portfolios

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.015*	-0.004	-0.005	-0.022***	-0.007*	0.005	-0.007	-0.004	0.010*
	(0.008)	(0.008)	(0.004)	(0.007)	(0.004)	(0.004)	(0.008)	(0.008)	(0.005)
RMRF	0.770***	1.119***	1.002***	1.047***	0.971***	0.981***	0.233	-0.140	-0.022
	(0.232)	(0.182)	(0.079)	(0.202)	(0.093)	(0.094)	(0.230)	(0.194)	(0.122)
SMB	0.007	-0.031	0.053*	0.225**	0.179***	0.080**	0.224*	0.211**	0.024
	(0.117)	(0.082)	(0.028)	(0.104)	(0.043)	(0.034)	(0.116)	(0.087)	(0.044)
HML	-0.005	0.018	0.005	-0.148**	-0.084**	-0.014*	-0.146*	-0.101	-0.019*
	(0.076)	(0.063)	(0.006)	(0.067)	(0.033)	(0.008)	(0.075)	(0.067)	(0.010)
N	65	195	780	65	195	780	65	195	780
R^2	0.159	0.174	0.181	0.338	0.392	0.130	0.076	0.036	0.005

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Appendix 2c. Regression results with AF based on 10 portfolios

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.011**	-0.006	0.001	-0.008	0.001	0.002	0.003	0.007	0.000
	(0.006)	(0.004)	(0.004)	(0.005)	(0.004)	(0.002)	(0.008)	(0.005)	(0.004)
RMRF	0.857***	1.176***	1.103***	1.167***	1.064***	1.092***	0.310	-0.112	-0.011
	(0.162)	(0.106)	(0.084)	(0.154)	(0.084)	(0.042)	(0.226)	(0.117)	(0.090)
SMB	-0.071	0.030	0.074**	0.166**	-0.047*	-0.017	0.237**	-0.077**	-0.091***
	(0.077)	(0.034)	(0.029)	(0.073)	(0.027)	(0.014)	(0.107)	(0.038)	(0.031)
HML	0.050	-0.008	-0.008	-0.092**	0.038**	0.005	-0.142**	0.046*	0.013
	(0.044)	(0.022)	(0.008)	(0.042)	(0.017)	(0.004)	(0.062)	(0.024)	(0.008)
N	60	180	720	60	180	720	60	180	720
R^2	0.418	0.479	0.242	0.587	0.552	0.551	0.135	0.043	0.016

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Appendix 3. Mean SPS in High and Low SPS split within portfolio 1 (SHORT) and 5 (LONG) across methods

	High SPS	Low SPS	t-stat diff
Time-series			
SHORT	0.349	0.035	54.94
LONG	0.378	0.036	40.95
Seasonal martingale			
SHORT	0.356	0.037	61.97
LONG	0.336	0.034	71.75
Analyst forecast			
SHORT	0.374	0.036	37.57
LONG	0.379	0.035	31.73
Event-window return			
SHORT	0.354	0.036	71.32
LONG	0.359	0.036	65.82

Note: The table presents the mean SPS in each LONG and SHORT portfolio across the four methodologies TS, MG, AF and RB, divided by HIGH and LOW SPS, and their t-stat difference between HIGH and LOW.

Appendix 4. Probability of BHAR prediction by chance for each method

	Number of observations	Number of successes (% of total)	Probability by chance
Time-series			
SHORT	2,161	868 (40.2)	44.5%
LONG	1,420	539 (38.0)	81.4%
Seasonal martingale			
SHORT	2,357	1,095 (46.0)	0.0%
LONG	3,122	1,244 (39.8)	57.6%
Analyst forecast			
SHORT	1,373	561 (40.9)	26.6%
LONG	1,186	513 (43.3)	1.2%
Event-window return			
SHORT	3,487	1,728 (49.6)	0.0%
LONG	3,030	1,379 (45.5)	0.0%

Note: The table presents the number of observations in the extreme portfolios LONG and SHORT across the four earnings estimation methodologies TS, MG, AF and RB. Number of successes refers to the number of observations with a BHAR over the upcoming 12 months from formation date that is in top (bottom) 40% for the full sample, represented in the LONG (SHORT) portfolio. The probability by chance is calculated using the cumulative binomial distribution function:

$\Pr(X \leq k) = \sum_{i=1}^{k} \binom{n}{k} p^i (1-p)^{n-i}$ *where k = number of observations – number of successes,*
n = number of observations and p = 1 – 40% = 60%.

Appendix 5a. Regression results with 5 days event-window with TS

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.014***	-0.004	-0.001	-0.004	-0.002	-0.004*	0.010	0.002	-0.004
	(0.005)	(0.003)	(0.002)	(0.011)	(0.004)	(0.002)	(0.010)	(0.004)	(0.002)
RMRF	0.878***	0.968***	0.852***	0.914***	0.888***	0.969***	0.036	-0.080	0.117**
	(0.148)	(0.068)	(0.037)	(0.334)	(0.093)	(0.046)	(0.317)	(0.097)	(0.048)
SMB	0.362***	0.062**	0.030**	0.179	-0.028	0.020	-0.183	-0.090**	-0.010
	(0.126)	(0.029)	(0.013)	(0.284)	(0.040)	(0.015)	(0.269)	(0.042)	(0.017)
HML	-0.207***	-0.023	0.000	-0.086	0.044*	0.006	0.122	0.067**	0.006
	(0.073)	(0.019)	(0.003)	(0.165)	(0.025)	(0.004)	(0.156)	(0.027)	(0.004)
N	58	174	696	58	174	696	58	174	696
R^2	0.464	0.589	0.478	0.150	0.410	0.453	0.018	0.049	0.014

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Appendix 5b. Regression results with 5 days event-window with MG

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.007	-0.003	-0.002	-0.005	0.001	0.004*	0.001	0.004	0.006**
	(0.005)	(0.005)	(0.002)	(0.005)	(0.003)	(0.002)	(0.005)	(0.005)	(0.003)
RMRF	1.223***	1.067***	0.962***	1.180***	0.973***	1.003***	-0.107	-0.102	0.050
	(0.170)	(0.110)	(0.050)	(0.143)	(0.070)	(0.051)	(0.164)	(0.129)	(0.068)
SMB	-0.043	0.103*	0.057***	0.131*	0.087**	0.059***	0.184**	-0.014	-0.001
	(0.089)	(0.055)	(0.018)	(0.076)	(0.036)	(0.018)	(0.086)	(0.064)	(0.024)
HML	-0.032	-0.080*	-0.001	-0.120**	-0.046	-0.009**	-0.094	0.033	-0.008
	(0.064)	(0.044)	(0.004)	(0.054)	(0.029)	(0.004)	(0.062)	(0.051)	(0.005)
N	65	195	780	65	195	780	65	195	780
R^2	0.467	0.334	0.330	0.530	0.507	0.334	0.080	0.005	0.003

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Appendix 5c. Regression results with 5 days event-window with AF

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.011**	-0.006**	-0.004*	-0.001	0.003	0.001	0.010**	0.009***	0.004*
	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)	(0.004)	(0.004)	(0.002)
RMRF	1.047***	1.100***	1.129***	1.181***	1.102***	1.080***	0.134	0.002	-0.049
	(0.153)	(0.074)	(0.050)	(0.129)	(0.062)	(0.030)	(0.127)	(0.082)	(0.052)
SMB	0.198	0.010	0.035**	0.117	-0.032	0.005	-0.081	-0.042	-0.031*
	(0.158)	(0.036)	(0.017)	(0.134)	(0.030)	(0.010)	(0.131)	(0.040)	(0.018)
HML	-0.102	0.015	-0.000	-0.070	0.026	0.004	0.033	0.011	0.004
	(0.093)	(0.023)	(0.004)	(0.078)	(0.019)	(0.002)	(0.077)	(0.025)	(0.004)
N	60	180	720	60	180	720	60	180	720
R^2	0.471	0.576	0.428	0.613	0.660	0.655	0.049	0.008	0.005

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Appendix 6a. Regression results with TS based on common sample

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	0.000	0.002	0.002	-0.009*	-0.006*	-0.004*	-0.009	-0.007**	-0.007**
	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.003)
RMRF	0.895***	1.009***	0.982***	1.155***	0.974***	1.044***	0.261	-0.036	0.062
	(0.144)	(0.069)	(0.038)	(0.151)	(0.074)	(0.052)	(0.169)	(0.083)	(0.058)
SMB	0.034	0.018	0.023*	0.055	-0.037	0.001	0.021	-0.055**	-0.022
	(0.052)	(0.021)	(0.012)	(0.055)	(0.022)	(0.017)	(0.062)	(0.025)	(0.019)
HML	-0.025	-0.010	-0.006*	-0.023	0.040***	0.011**	0.002	0.049***	0.017***
	(0.030)	(0.013)	(0.003)	(0.031)	(0.014)	(0.004)	(0.035)	(0.016)	(0.005)
N	58	174	696	58	174	696	58	174	696
R^2	0.469	0.603	0.545	0.580	0.568	0.430	0.077	0.069	0.023

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Table 6b. Regression results with MG based on common sample

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.002	-0.002	-0.001	-0.003	-0.003	-0.001	-0.001	-0.001	-0.000
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.002)	(0.007)	(0.005)	(0.004)
RMRF	0.765***	1.100***	1.154***	1.008***	1.052***	1.048***	0.243	-0.048	-0.106
	(0.133)	(0.091)	(0.080)	(0.119)	(0.089)	(0.046)	(0.187)	(0.105)	(0.087)
SMB	-0.078	0.022	0.019	0.162**	0.115**	0.032**	0.240**	0.093*	0.013
	(0.078)	(0.045)	(0.027)	(0.070)	(0.044)	(0.016)	(0.110)	(0.052)	(0.029)
HML	0.042	-0.013	0.007	-0.093**	-0.057**	-0.0001	-0.135**	-0.043	-0.008
	(0.044)	(0.027)	(0.007)	(0.040)	(0.027)	(0.004)	(0.062)	(0.031)	(0.008)
N	58	174	696	58	174	696	58	174	696
R^2	0.462	0.525	0.279	0.637	0.512	0.487	0.124	0.027	0.005

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Table 6c. Regression results with AF based on common sample

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.008*	-0.006*	-0.003*	0.001	0.001	0.000	0.009**	0.007**	0.03
	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)
RMRF	0.909***	1.032***	1.089***	1.274***	1.091***	1.096***	0.165	-0.041	-0.013
	(0.125)	(0.078)	(0.057)	(0.118)	(0.067)	(0.034)	(0.153)	(0.083)	(0.061)
SMB	0.018	0.035	0.047**	0.103*	-0.022	0.006	0.086	-0.040	-0.032
	(0.063)	(0.030)	(0.012)	(0.059)	(0.026)	(0.012)	(0.077)	(0.032)	(0.021)
HML	-0.004	-0.020	-0.004	-0.060*	0.017	0.005	-0.056	0.037*	0.009
	(0.036)	(0.018)	(0.005)	(0.034)	(0.015)	(0.003)	(0.044)	(0.019)	(0.005)
N	58	174	696	58	174	696	58	174	696
R^2	0.560	0.571	0.401	0.663	0.666	0.652	0.099	0.009	0.009

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Appendix 7a. Calendar-time regression results with TS

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.017	-0.014**	-0.006*	-0.015	-0.013**	-0.005	0.002	0.000	0.002
	(0.011)	(0.006)	(0.003)	(0.011)	(0.005)	(0.004)	(0.015)	(0.008)	(0.004)
RMRF	0.542**	0.813***	0.738***	0.748***	1.056***	0.906***	0.205	0.242	0.168**
	(0.234)	(0.131)	(0.054)	(0.234)	(0.122)	(0.059)	(0.326)	(0.176)	(0.071)
SMB	0.401	0.294**	0.058**	-0.170	0.373***	0.065**	-0.571	0.079	0.007
	(0.331)	(0.143)	(0.026)	(0.330)	(0.133)	(0.029)	(0.461)	(0.193)	(0.035)
HML	0.949***	0.141	0.005	0.387	-0.003	-0.001	-0.562	-0.143	-0.005
	(0.322)	(0.175)	(0.006)	(0.321)	(0.163)	(0.007)	(0.447)	(0.236)	(0.008)
N	58	174	696	58	174	696	58	174	696
R^2	0.617	0.450	0.310	0.619	0.569	0.356	0.108	0.019	0.013

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Table 7b. Calendar-time regression results with MG

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	-0.012	-0.012	-0.006	-0.022***	-0.016***	-0.001	-0.005	-0.004	0.007
	(0.012)	(0.007)	(0.004)	(0.007)	(0.005)	(0.003)	(0.013)	(0.009)	(0.005)
RMRF	0.993***	0.973***	0.951***	0.716***	0.903***	0.901***	-0.348	-0.104	-0.041
	(0.288)	(0.168)	(0.071)	(0.161)	(0.124)	(0.060)	(0.320)	(0.197)	(0.085)
SMB	-0.020	-0.001	0.077**	0.244*	0.297***	0.100***	0.294	0.311**	0.027
	(0.233)	(0.108)	(0.032)	(0.133)	(0.081)	(0.028)	(0.258)	(0.127)	(0.039)
HML	0.269	0.076	0.005	0.333	0.115	-0.010	0.031	0.031	-0.015*
	(0.368)	(0.186)	(0.007)	(0.212)	(0.139)	(0.006)	(0.409)	(0.217)	(0.009)
N	65	195	780	65	195	780	65	195	780
R^2	0.450	0.293	0.248	0.688	0.461	0.276	0.103	0.050	0.005

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Table 7c. Calendar-time regression results with AF

	SHORT			LONG			PEAD-position		
Variables	1M	3M	12M	1M	3M	12M	1M	3M	12M
Intercept	0.010	-0.004	-0.004	0.003	0.001	0.003	-0.014	0.003	0.007*
	(0.024)	(0.010)	(0.003)	(0.008)	(0.005)	(0.002)	(0.023)	(0.011)	(0.004)
RMRF	1.406**	1.238***	1.111***	0.647***	1.047***	1.063***	-0.444	-0.016	-0.003
	(0.580)	(0.233)	(0.059)	(0.203)	(0.121)	(0.043)	(0.563)	(0.255)	(0.067)
SMB	-1.000	-0.037	0.039	-0.527*	0.010	0.006	0.918	0.256	-0.037
	(0.783)	(0.239)	(0.027)	(0.275)	(0.122)	(0.020)	(0.760)	(0.262)	(0.030)
HML	0.372	0.213	0.002	0.536*	-0.076	-0.004	0.017	-0.356	-0.003
	(0.853)	(0.288)	(0.006)	(0.309)	(0.152)	(0.005)	(0.828)	(0.315)	(0.007)
N	60	180	720	60	180	720	60	180	720
R^2	0.487	0.364	0.473	0.675	0.515	0.586	0.150	0.031	0.007

*Note: Regression results for the holding periods of 1 month, 3 months and 12 months are presented in the table. All control variables have been adjusted to their corresponding holding period. RMRF represents the return of the market over the risk-free rate. SMB represents the size factor of the Fama-French three-factor model and the HML variable represents the value premium factor. Standard errors in parentheses, stars indicate significance level, *** p<0.01, ** p<0.05, * p<0.1*

Appendix 8a. Descriptive statistics of firm characteristics for the TS sample

Variables	N	Mean	Median	Std. Dev.	Skewness	Kurtosis
Assets	9,259	12,277	837	40,406	5.92	43.83
Debt	9,259	7,463	383	26,112	7.00	64.41
Equity	9,267	4,739	400	15,517	5.83	42.31
Market Cap	9,266	12,912	832	42,355	6.13	49.65
M/B	9,263	9.12	2.34	45.11	9.44	90.59
Debt/Equity	9,259	1.97	1.08	65.98	9.50	80.04
Debt/Assets	9,259	0.51	0.52	0.24	4.44	22.62

Note: descriptive statistics for the 404 unique firms in the TS sample. All accounting variables are measured at the end of each quarter. Market cap is measured as the closing market capitalization on the last day of the quarter. M/B is the market cap divided by the book value of owners' equity. All values in MSEK.

Appendix 8b. Descriptive statistics of firm characteristics for the MG sample

Variables	N	Mean	Median	Std. Dev.	Skewness	Kurtosis
Assets	14,052	10,368	679	36,027	6.39	51.49
Debt	14,052	6,252	321	23,006	7.58	76.85
Equity	14,060	4,023	325	14,066	6.35	50.09
Market Cap	14,087	10,692	720	38,420	6.91	62.02
M/B	14,060	8.66	2.43	372.91	11.86	126.20
Debt/Equity	14,050	1.84	1.04	54.41	11.64	128.94
Debt/Assets	14,052	0.50	0.51	0.21	0.59	12.81

Note: descriptive statistics for the 573 unique firms in the MG sample. All accounting variables are measured at the end of each quarter. Market cap is measured as the closing market capitalization on the last day of the quarter. M/B is the market cap divided by the book value of owners' equity. All values in MSEK.

Table 8c. Descriptive statistics of firm characteristics for the AF sample

Variables	N	Mean	Median	Std. Dev.	Skewness	Kurtosis
Assets	5,175	19,868	2,832	49,533	4.70	29.46
Debt	5,175	12,065	1,553	32,146	5.64	43.95
Equity	5,175	7,678	1,186	18,929	4.41	25.29
Market Cap	5,175	21,141	3,469	52,433	4.78	31.12
M/B	5,175	11.63	2.589	50.12	8.67	145.93
Debt/Equity	5,175	2.14	1.229	7.89	8.88	128.46
Debt/Assets	5,175	0.53	0.55	0.18	-0.12	3.99

Note: descriptive statistics for the 366 unique firms in the AF sample. All accounting variables are measured at the end of each quarter. Market cap is measured as the closing market capitalization on the last day of the quarter. M/B is the market cap divided by the book value of owners' equity. All values in MSEK.

Table 8d. Descriptive statistics of firm characteristics for the RB sample

Variables	N	Mean	Median	Std. Dev.	Skewness	Kurtosis
Assets	16,091	10,118	640	35,341	6.69	58.29
Debt	16,090	6,041	299	22,681	8.01	87.43
Equity	16,091	3,984	305	13,762	6.25	49.19
Market Cap	16,122	10,409	691	37,267	6.97	63.83
M/B	16,042	8.08	2.43	33.32	12.25	136.21
Debt/Equity	16,090	1.73	1.04	4.66	12.73	130.81
Debt/Assets	16,090	0.49	0.51	0.24	4.71	113.92

Note: descriptive statistics for the 618 unique firms in the RB sample. All accounting variables are measured at the end of each quarter. Market cap is measured as the closing market capitalization on the last day of the quarter. M/B is the market cap divided by the book value of owners' equity. All values in MSEK.

Appendix 9. List of variables and sources in the paper

Data source	Frequency	Variable name	Description
Eikon	Quarterly	EPS report date fiscal period end	Quarterly earnings announcement date
Eikon	Quarterly	EPS basic fiscal	Reported quarterly earnings per share
Eikon	Quarterly	Median forecasted EPS	The median estimate of earnings per share presented by analysts reporting to I/B/E/S
FinBas	Daily	Lastadj	Daily closing stock price adjusted for dividends to enable comparable time-series analysis
FinBas	Quarterly	Market capitalization	Total market capitalization of all stock classes outstanding for a firm
SHoF Data Center	Daily	rf	The daily risk-free rate, proxied by 1-month Swedish t-bill
SHoF Data Center	Daily	rm	Daily market return, proxied by SIXRX index
SHoF Data Center	Daily	rmrf	Market return less risk-free rate
SHoF Data Center	Daily	SMB	Daily risk premium for small stocks over big stocks
SHoF Data Center	Daily	HML	Daily risk premium for value stocks over growth stocks
Compustat Global	Quarterly	GSECTOR	Two-digit classification of industry as defined by general industry classification (GIC)
Compustat Global	Quarterly	ATQ	Reported quarterly total assets
Compustat Global	Quarterly	LTQ	Reported quarterly total liabilities, used as debt in paper
Compustat Global	Quarterly	TEQQ	Reported quarterly total equity

Note: The table presents the data collected.