

Short and Sweet: The Informational Advantage Behind Short Sellers' Returns

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Abstract

This paper investigates the informational advantage underpinning short sellers' abnormal returns, focusing on the drivers of the widely observed negative relationship between Relative Short Interest (RSI) and future stock returns. We assess whether short sellers profit by systematically exploiting publicly known market anomalies, anticipating earnings surprises, and/or reacting efficiently to earnings announcements. Using a novel and comprehensive dataset of Nordic equities from 2020–2025, enabled by EU short selling disclosure regulations, we find that short sellers actively target stocks with strong negative anomaly signals to generate abnormal returns, with a portfolio on the short leg of RSI delivering a negative and significant next-month alpha of 0.78%. Moreover, RSI significantly predicts earnings surprises and is highly informative during earnings announcement months, highlighting both anticipatory and reactive informational advantages.

Keywords: Relative Short Interest (RSI), RSI-Return Relationship, Market Anomalies, Composite Measure of Anomalies (PERC), Abnormal Returns, Short Sale Constraints, Earnings Surprises, Earnings Announcements.

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1 Introduction

Short selling is a topic of interest in financial economics due to its unique risk profile and the persistent ability of certain short sellers to generate abnormal returns. Unlike long investors, short sellers face asymmetric payoffs, high execution costs, and frequent regulatory scrutiny, and yet many still manage to outperform. This raises a natural and compelling question: How do short sellers make money? Understanding what drives short sellers' profitability is not only relevant for assessing the efficiency of capital markets, but also for clarifying the informational role that short sellers play in the pricing process.

A robust empirical finding in this area is the negative relationship between Relative Short Interest (RSI), the proportion of shares sold short relative to shares outstanding, and future stock returns. This relationship, documented across various markets and time periods (Desai et al., 2002; Diether et al., 2009; Rapach et al., 2016), suggests that stocks with higher short interest tend to underperform in the following months. The persistence and magnitude of this pattern challenge traditional asset pricing models and imply that short sellers may possess, or be able to generate, valuable information about mispricing or deteriorating firm prospects.

This paper centers on understanding the drivers of the RSI–return relationship. Specifically, we ask whether short sellers' abnormal returns are explained by their systematic targeting of stocks with known pricing anomalies, their ability to anticipate future earnings surprises, or their capacity to respond more efficiently to public firm-specific news releases. In doing so, we aim to clarify the nature of short sellers' informational edge: do they profit by better exploiting publicly available information, suggesting they are informed and sophisticated?

To better understand the mechanisms behind the RSI-return relationship, we test three interrelated hypotheses. Hypothesis 1 posits that short sellers generate abnormal returns by systematically exploiting publicly observable anomalies, targeting firms with strong negative signals across measures such as accruals, asset growth, and profitability. This builds on findings from Dechow et al. (2001), Stambaugh et al. (2012) and Wu and Zhang (2019), who argue that short sellers derive informational advantages from their ability to process complex accounting-based data. Hypothesis 2 explores whether short sellers anticipate future earnings surprises, as suggested by Boehmer et al. (2008) and Akbas et al. (2017). Hypothesis 3 examines whether short sellers respond more efficiently to public news events, particularly earnings announcements, as proposed by Engelberg et al. (2012). Together, these hypotheses seek to clarify whether the predictive power of RSI can be explained by exposure to known mispricing signals, superior forecasting of

earnings-related information, or responsiveness to firm-specific news.

To investigate these hypotheses, we leverage a proprietary dataset enabled by a regulatory shift under the EU Short Selling Regulation, which requires national financial authorities to disclose both public short positions exceeding the 0.5% threshold and anonymous aggregate short interest for all listed firms, making this data available from 2020 for a majority of the Nordic stock exchanges (European Parliament and Council of the European Union, 2012). This results in comprehensive, systematic coverage of short selling across Denmark, Finland, and Sweden, with consistent monthly data and minimal reporting gaps[1]. The Nordic stock markets, characterized by regulatory uniformity, consequently provides a high-quality empirical setting to study systematically disclosed short selling activity. Our final dataset spans 2020–2025 and includes over 15,000 firm-month observations, combining Relative Short Interest (RSI) data with firm fundamentals, market returns, and earnings announcements. This allows us to directly test the informational role of short sellers in a Nordic setting.

Our empirical strategy aligns with our three core hypotheses and involves a combination of portfolio analyses and Fama and MacBeth (1973) regressions. First, to test whether short sellers exploit known mispricing signals, we construct a composite anomaly score (*PERC*) based on 11 established pricing anomalies and assess how stock returns vary across portfolios sorted by RSI and *PERC*. Moreover, we run regressions on the predictive power of RSI and *PERC* on next-month returns as well as a regression on how *PERC* explains RSI. Second, we run Fama-MacBeth regressions to examine the predictive power of RSI on future earnings surprises, controlling for anomaly exposure and short sale constraints such as firm size and illiquidity. These regressions allow us to isolate the informational content of short interest beyond that captured by public anomaly signals. Third, we analyze whether RSI becomes more informative around earnings announcements by interacting RSI with event dummies in additional Fama-MacBeth regressions. We complement this with a double-sorting approach based on RSI and the presence, and direction, of earnings announcements to assess whether abnormal returns are concentrated during key public news events.

Our findings offer several contributions to the academic literature. First, we document that a substantial part of the RSI–return relationship can be explained by short sellers' exposure to public anomaly signals, supporting the idea that short sellers act as anomaly arbitrageurs. Second, we find that RSI predicts earnings surprises, suggesting that short sellers are able to anticipate future firm performance. This holds also after controlling

[1]Norwegian firms are included in the original sample but do not report total RSI, leading to their exclusion from our dataset. Also, we exclude the Iceland stock exchange due to its limited market size and lower trading volume, which could compromise data consistency and comparability.

for the part of the RSI that is explained by anomaly signals. Third, we show that RSI is especially informative during earnings announcement months, particularly on the short leg of RSI, implying that short sellers react effectively to new information. This finding also holds when controlling for anomalies. These findings highlight that anomaly and earnings mechanisms are complementary in explaining the negative RSI-return relationship. Finally, our results suggest that the predictive power of short interest is attenuated in the presence of short sale constraints.

In total, we provide support for the existing literature by finding that short sellers generate abnormal returns by (a) exploiting anomaly signals, (b) predicting future earnings, and (c) reacting to earnings announcements. Moreover, we extend the literature by showing that abnormal returns related to earnings mechanisms are complementary to anomalies in explaining short sellers' abnormal returns. Overall, by integrating insights from anomaly pricing, earnings forecasting, and information processing, this paper offers a nuanced and empirically grounded understanding of the role short sellers play in modern financial markets.

2 Literature Review and Hypothesis

2.1 Background

There is a documented negative relationship in the financial literature between short selling and equity returns. Desai et al. (2002); Figlewski (1981); Aitken et al. (1998); Diether et al. (2009) find a relationship between Relative Short Interest (RSI) and returns, while Rapach et al. (2016) find that this relationship is also prevalent for aggregate-level short interest. Additionally, Boehmer et al. (2008) examine whether daily shorting flows systematically predict stock returns and find that they do. The persistent negative relationship means that more heavily shorted stocks yield lower subsequent returns. One explanation for this relationship in which the negative RSI-return relationship is attributed to short sale constraints is developed by Miller (1977) in a highly influential article. He hypothesizes that if short sellers are prevented from expressing their opinion on the fair price of a stock in the market, the price will be biased towards the upside. This hypothesis is tested extensively in a wide array of articles, with conflicting results. In these, multiple different proxies for short sale constraints are used, discussed in more detail in Section 2.2. If, as many of the articles outlined below suggest, short sale constraints are not sufficient to account for the entire negative RSI-return relationship, an alternative explanation is that short sellers possess an informational advantage, enabling them to generate abnormal returns. This is examined more in Sections 2.3 and 2.4 of the literature review.

2.2 Negative RSI-return relationship explained by short sale constraints

Figlewski (1981) tests Miller's hypothesis, which suggests that short sale constraints cause upward price biases, by using RSI as a proxy for short sale constraints. He argues that firms with the highest RSI should be the most difficult to short, since the level of unobserved demand to short a stock should rise together with the observed demand. In finding that more heavily shorted firms yield lower subsequent returns, Figlewski concludes that stocks with more short sale restrictions are overpriced, providing support for Miller's hypothesis. Another commonly used proxy for short sale constraints is the level of institutional ownership, reflecting the supply side of short selling. Asquith et al. (2005) argue that when institutional ownership is low, the supply of shares available for borrowing is limited, making short selling more costly. They find that for most stocks, institutional ownership exceeds short interest, suggesting that short sale constraints are generally not binding.

D'Avolio (2002) directly measures borrowing difficulty using an 18-month database from a single lender, finding that only 9% of stocks are hard to borrow with loan fees exceeding the fed funds rate. This suggests that most stocks face no short sale constraints, and the negative RSI-return relationship for these stocks cannot be attributed to short selling barriers. An alternative explanation is that short sellers are more often correct than wrong. One source of support for this view is provided by Cohen et al. (2007). They examine monthly changes in RSI and conclude that negative returns observed after increases in RSI remain large after accounting for transaction costs, implying that the negative relationship between short selling and returns survives exposure to short sale constraints. While proxies such as institutional ownership offer insight into short sale constraints, they do not capture the full range of frictions. As Shiller (2003) notes, psychological barriers, social stigma, and regulatory pressures can also significantly deter short selling, despite being difficult to quantify.

2.3 Short sellers as informed traders

If short sale constraints are insufficient to explain the widely documented negative RSI-return relationship, an alternative explanation is that short sellers are, on average, informed traders. This view is supported by Diamond and Verrecchia (1987), who argue that the cost of shorting, even for stocks without short sale constraints as defined by D'Avolio (2002), reduces the likelihood that short sellers are merely liquidity traders. Consequently, short sellers are more likely to be informed traders, leading to a high degree of informativeness in the amount short interest. As a result, elevated short interest should convey negative information about a stock, thereby implying a negative relationship between short interest and subsequent returns. Furthermore, Boehmer et al. (2008) demonstrate that short selling flows predict negative future returns, suggesting that short sellers act on information that has not yet been incorporated into stock prices. The aforementioned studies suggest that the abnormal returns generated by short sellers are largely attributable to their informational advantage. However, they do not provide a concrete explanation for the specific nature of this informativeness. The natural follow-up question is: In what sense are short sellers informed? The informativeness can be broadly attributed to two explanations, namely that (a) short sellers possess a superior ability to process publicly available information, or (b) they have access to private information not available to other investors. If (a) holds true, an additional question emerges: What makes up their superior information processing ability?

2.4 How are short sellers informed?

Drawing on the negative RSI-return relationship, a branch of literature attempts to explain in concrete terms how short sellers are informed. Wu and Zhang (2019), from whom we take methodological inspiration, find that a significant share of short sellers' profits is made by exploiting publicly available market anomalies. The relationship between Relative Short Interest (RSI) and 18 widely published anomalies, as well as a composite measure of these anomalies, is tested in a series of statistical tests. In one of these tests, in which a double-sorting portfolio methodology is adopted, they find that the negative RSI-return relationship for stocks both on the short leg of RSI and anomalies has a greater magnitude than stocks on the short leg of RSI but on the long leg of anomalies. This implies that the abnormal returns of short sellers are at least partially explained by exploitation of publicly available anomalies. The findings of Wu and Zhang (2019) support Dechow et al. (2001), who also find that short sellers utilize return-predictive anomalies found in accounting variables when constructing trading strategies. Similarly, Stambaugh et al. (2012) show that short sellers' exploitation of mispricing signals, defined by 11 anomalies, is significantly elevated during periods following high market sentiment. Finally, Chen et al. (2022) find that short selling efficiency, a measure of how short selling is aligned with mispricing anomalies, predicts future stock return. This implies that short sellers exploit anomalies to generate abnormal returns. Building on these findings, we formulate our first hypothesis as follows:

Hypothesis 1: Short sellers generate abnormal returns by systematically exploiting publicly observable market anomalies.

Another possible explanation of short sellers' informativeness is their ability to predict and react to future earnings and news events. Wu and Zhang (2019); Boehmer et al. (2020) find that short sellers predict unexpected earnings. Akbas et al. (2017) attribute this to short sellers' ability to predict news rather than access to private information while Karpoff and Lou (2010) suggest that short sellers predict financial misconduct before it becomes public. Moreover, Christophe et al. (2004) examine short sale transactions five days prior to earnings announcements and find a strong relationship between pre-announcement short selling and post-announcement stock return, linking this to short sellers' ability to anticipate earnings. In the light of these findings, our second hypothesis is formulated as follows:

Hypothesis 2: Short sellers generate abnormal returns by predicting future earnings surprises, and their predictive power extends beyond the active use of public anomaly signals.

Another possible explanation for short sellers' abnormal profits is their superior ability to react to public news events. Engelberg et al. (2012) provide support for this by finding that a significant portion of short sellers' profits is made around news events. They therefore conclude that short sellers' abnormal returns can be attributed to their ability to process publicly available information. This article provides the backdrop against which we formulate our third hypothesis:

Hypothesis 3: Short sellers generate abnormal returns by efficiently reacting to earnings announcement news.

In the following sections, we outline the methodology underlying our analysis, followed by a presentation of the empirical results, which includes discussion of the key findings. We conclude with a summary of our main insights, a reflection on the study's limitations, and suggestions for future research.

3 Data and Variables

Our sample contains all stocks currently listed on the Copenhagen Stock Exchange, Helsinki Stock Exchange, Oslo Stock Exchange, Stockholm Stock Exchange, and First North Growth Market in the Compustat Global database from 2019 to 2025[2]. In line with the asset pricing literature (Fama and French, 2008), we exclude financial firms with SIC codes between 6000 and 6999. Following Boehme et al. (2006), we impose an illiquidity screen excluding firm-month observations exceeding the 95th percentiles in terms of illiquidity. Hirshleifer et al. (2011) show that greater liquidity reduces the price impact and short squeeze risk faced by short sellers; highly illiquid stocks are more vulnerable to bid-ask bounce, limited trading activity, and short selling constraints, which could distort our results. Illiquidity is measured using the illiquidity ratio ($ILLIQ$) from Amihud (2002).[3]

Quarterly fundamentals data is obtained from Compustat. Short selling data is obtained with monthly frequency from the Holdings database provided by Modular Finance and includes Relative Short Interest (RSI), calculated as the ratio of the total number of shares sold short to the total shares outstanding at the month-end. Following the implementation of the EU Short Selling Regulation, detailed short selling data for Nordic firms is available from January 2020 (European Parliament and Council of the European Union, 2012). After filtering the data on (1) the requirement of firms having non-missing total Relative Short Interest (all positions exceeding 0.1%) and (2) the requirement of included months to have more than 50 firm observations, our dataset consists of 15,665 firm-months covering 457 firms and 57 months across the January 2020 to January 2025 period. Norwegian companies are excluded by construction due to the application of the 0.1% threshold filter, as short interest data in Norway is limited to publicly disclosed positions exceeding 0.5%, thereby precluding consistent measurement below the required level (see Section 3.3). Month t in each firm-month observation reflects monthly stock return, RSI at month-end, and fundamentals data from the most recent quarter.[4]

[2]We exclude the Iceland stock exchange due to its limited market size and lower trading volume, which could compromise data consistency and comparability

[3]We measure illiquidity as the average ratio of the daily absolute return to the dollar trading volume $x \times 10^6$ over the prior 12-month period ending in month $t-1$.

[4]I.e., in January, February, and March 2024, fundamentals reflect the fourth quarter of 2023. In our statistical analyses, anomaly variables based on fundamentals are further lagged, allowing the fundamentals data to be publicly available and reflected in the market.

3.1 Fundamentals & stock data

Daily stock data is obtained from the Compustat Global Security Daily database, accessed through the Wharton Research Data Services (WRDS). This data includes stock prices, number of shares outstanding and other stock-related data. Daily stock data enables us to calculate one-day returns at earnings announcement dates (see Section 4.3.2). For other tests, we use monthly stock data. Monthly stock returns are computed using the adjusted closing prices at the end of each month. Quarterly data on stock fundamentals, used in the calculation of several of the market anomalies and control variables, is retrieved online from the Compustat database, also accessed through WRDS. FactSet is used to obtain data on earnings announcement dates. These datasets have been merged by matching ISIN codes.

3.2 Market returns and risk-free interest data

Monthly market returns and a monthly risk-free rate are used in various regressions. Market returns for the respective stock exchanges are retrieved from Compustat Global Index Monthly Prices database, and we use the 1-month Euro Interbank Offered Rate (EURIBOR), obtained from the Finnish Central Bank, as the risk-free rate to match the monthly return frequency and ensure consistency in excess return calculations.

3.3 Short selling data

For data on short selling, monthly Relative Short Interest (RSI) has been used, reported at the month-end. This data is retrieved for Nordic companies from January 2020 to January 2025. RSI is defined as the number of shares shorted at any given date divided by the total number of shares outstanding for a stock. This data is accessed through the Holdings database provided by Modular Finance. Holdings, in turn, obtains RSI data from the Financial Supervisory authority in each country, which reports data on short interest. Investors on the Danish, Finnish, and Swedish exchanges are required by the EU Short Selling Regulation (SSR) to report short interest above 0.1% to the respective Financial Supervisory Authority (European Parliament and Council of the European Union, 2012). Data for total Relative Short Interest, defined as the sum of all net short positions exceeding 0.1%, is thus available for all three countries since January 2020. Since Norway is not a member of the EU, only public short interest, defined as positions exceeding 0.5% RSI, is available for Norwegian stocks. Therefore, Norwegian stocks have been excluded from our dataset to maximize the comprehensiveness of our short selling

data[5].

3.4 Introducing the anomalies

We examine 11 widely established and published market anomalies, out of which 10 are based on the 11 anomalies used in Stambaugh et al. (2012), Stambaugh and Yuan (2017), and Chen et al. (2022). In Stambaugh et al. (2012), these anomalies are tested and survive exposure to the Fama-French three-factor model (Fama and French, 1992), which provides strong empirical support for the existence of the 11 anomalies. We do not include the *Financial Distress* variable from Stambaugh et al. (2012) due to data constraints. However, this is not expected to have a significant effect on our results, since the other financial distress variable from Stambaugh et al. (2012), *Ohlson's O-Score*, is included. Also, to account for the well-documented value anomaly, we include a book-to-market variable (Stattman, 1980; Rosenberg et al., 1985). For anomalies based on periodic accounting data, we use last-twelve-month figures, unless explicitly stated otherwise, to ensure consistency and comparability across firms and time.

1. Book-to-market (BM)
Stattman (1980) and Rosenberg et al. (1985) showed the existence of a significant return premium for stocks with a high book-to-market value. This was one of the first formal critiques of the Efficient Market Hypothesis and was later adopted as an additional risk factor in a paper by Fama and French (1992). The book-to-market variable is calculated as the book value of equity in the most recent reporting quarter divided by market capitalization. The accounting information used is from the quarter that ends at least four months before t, to ensure public availability of the data.

2. Ohlson's O-Score (O-Score)
Ohlson (1980) shows that firms with a greater probability of bankruptcy yield lower subsequent returns. Ohlson's O-Score is a distress measure based on a static model predicting a firm's bankruptcy based on accounting variables. The model is presented in the equation below and the definitions of the variables included in the equation can be found in Table 1. The accounting information used is from the quarter that ends at least four months before t, to ensure public availability of the data.

$$\text{O} = \text{-0.407} \times SIZE + 6.03 \times TLTA - 1.43 \times WCTA + 0.076 \times CLCA - 1.72 \times OENEG - 2.37 \times NITA - 1.83 \times FUTL + 0.285 \times INTWO - 0.521 \times CHIN - 1.32$$

[5]To maximize the coverage of short interest in our analysis, we choose to focus on total Relative Short Interest (RSI), leading to the exclusion of Norwegian stocks from the study. For instance, in December 2024, Nibe Industrier B had a total RSI of 9.28%, while its public RSI was only 3.61%, illustrating that total RSI offers a more comprehensive measure of short selling activity.

Table 1: Ohlson O-Score Variable Definitions

Variable	*Definition*
SIZE	log(Total Assets)
TLTA	Total Debt / Total Assets
WCTA	Working Capital / Total Assets
CLCA	Current Liabilities / Current Assets
OENEG	1 if Total Liabilities > Total Assets, 0 otherwise
NITA	Net Income / Total Assets
FUTL	Pre-tax Income / Total Liabilities
INTWO	1 if net loss for the eight quarters, 0 otherwise
CHIN	(Net Income$_q$ - Net Income$_{q-4}$) / |(Net Income$_q$+Net Income$_{q-4}$)|

3. Net Stock Issues (NSI)

The market for stock issues has long been regarded as producing a sentiment-driven anomaly. Managers tend to issue shares when stock prices are pushed high by sentiment-driven traders. Ritter (1991) supported this by showing that issuers of stocks generally underperform non-issuers with otherwise similar characteristics in years following the issues. Fama and French (2008) provided additional support to this by finding a negative correlation between Net Stock Issuance and subsequent stock returns. Net Stock Issuance is measured as the annual log change in the number of split-adjusted shares outstanding. The most recent reporting quarter used is the one that ends at least four months before t, to ensure public availability of accounting information.

4. Composite Equity Issues (CEI)

Daniel and Titman (2006) found support for issuers' stock underperformance using another measure than Ritter (1991), which they call Composite Equity Issues. They subtract the cumulative return of a stock from the total growth in its market capitalization. To calculate this measure, the 12-month cumulative stock returns are subtracted from the 12-month growth in market capitalization. The variable is lagged to represent the quarter that ends at least four months before t, to match the timing of the *Net Stock Issues* variable.

5. Total Accruals (TACC)

Sloan (1996) shows that firms with high levels of accruals significantly underperform firms with low levels of accruals. He attributes this to investors overestimating the persistence of accrual-based earnings. The Total Accruals variable is calculated as the annual change in non-cash working capital minus depreciation and amortization for the last twelve months.

This is then divided by average total assets for the preceding two years. Non-cash working capital is calculated as current assets less cash minus current liabilities less short-term debt. The accounting information used is from the quarter that ends at least four months before t, to ensure public availability of the data.

6. Net Operating Assets (NOA)
Hirshleifer et al. (2004) find that Net Operating Assets, defined as the difference between all operating assets and all operating liabilities, significantly predict negative long-term stock returns of stocks. The authors argue that this measure, equivalent to the cumulative difference between operating income and free cash flow, captures an investor bias to focus more on accruals-based accounting profitability rather than cash profitability. This measure is calculated as operating assets minus operating liabilities divided by total lagged assets. Operating assets is defined as total assets less cash and short-term investments whereas operating liabilities are defined as total liabilities less interest-bearing liabilities. The accounting information used is from the quarter that ends at least four months before t, to ensure public availability of the data.

7. Momentum (MOM)
The momentum variable effect became widespread after Jegadeesh and Titman (1993) showed that recent returns are a significant predictor of future returns. This is one of the most well-known and robust anomalies and has been widely used in academia since, including as a fourth anomaly variable in Carhart (1997) factor model. Following Carhart (1997), the momentum variable is constructed by calculating the cumulative 11-month return from $t - 11$ to t.

8. Gross Profitability Premium (GPP)
Novy-Marx (2013) shows that the Gross Profitability Premium, defined as the gross profit divided by total assets, is a positive predictor of abnormally high returns. He argues that gross profit is a particularly clean measure of economic profitability, since it is far up in the income statement, and therefore less polluted by items unrelated to profitability. The accounting information used is from the quarter that ends at least four months before t, to ensure public availability of the data.

9. Asset Growth (AG)
Cooper et al. (2008) find that abnormally high asset growth is a predictor of lower subsequent returns, attributing this to investors' initial overreliance on the quality of firms' asset investments. Asset growth is defined as the 12-month growth rate in total assets. The accounting information used is from the quarter that ends at least four months before t, to ensure public availability of the data.

10. Return on Assets (ROA)

Chen et al. (2011) show that return on assets yields abnormally high subsequent returns. Return on assets is calculated as the ratio of the most recent four quarters' cumulative Net Income divided by total assets. The accounting information used is from the quarter that ends at least four months before t, to ensure public availability of the data.

11. Investments-to-Assets (ITA)

Titman et al. (2004) found that investments-to-assets also predict subsequent negative returns. The authors argue that this is attributable to investors' initial underreaction to managers' empire-building behavior. Following Titman et al. (2004), Investments to assets are calculated as the annual change in gross property, plant, and equipment, plus annual change in inventory. This number is divided by the scaled book value of total assets to arrive at the variable. The accounting information used is from the quarter that ends at least four months before t, to ensure public availability of the data.

3.5 Control variables

In addition to the anomalies discussed above, we use two variables as proxies for short sale constraints. First, we include Market Capitalization ($MCAP$), measured in EUR as the number of shares outstanding times the close price on the last day of the month. Second, we also include an illiquidity ratio, $ILLIQ$. This was developed by Amihud (2002) and is defined as the average ratio of the daily absolute return to the dollar trading volume multiplied by 10^6 over the prior 12-month period ending in month $t-1$.

3.6 Summary statistics

Table 2: Summary statistics of RSI, anomalies, and control variables

	Mean	**Median**	**Std. Dev.**
RSI	1.35	0.52	2.01
BM	0.62	0.37	0.87
MOM	0.11	-0.02	0.76
O-Score	-0.16	-0.66	3.03
NSI	0.10	0.00	0.28
CEI	0.14	0.00	0.65
TACC	-0.02	-0.02	0.07
NOA	0.57	0.62	0.22
GPP	0.28	0.25	0.26
AG	0.27	0.08	0.98
ROA	-0.11	0.03	0.41
ITA	0.05	0.02	0.11
MCAP	2,607	431	5,764
ILLIQ	0.34	0.11	0.54

Note: This table reports the time series average of cross-sectional mean, median, and standard deviation for RSI, eleven anomaly variables, and the two control variables during the sample period of 2020 - 2025. All anomaly variables are defined in Section 3.4. All continuous variables are winsorized at the 0.5 and 99.5 percentiles. *MCAP* is in EUR.

Table 2 presents summary statistics for RSI and the 11 anomaly variables included in this study. All continuous variables are winsorized at the 0.5th and 99.5th percentiles to reduce the influence of extreme values. The average Relative Short Interest is 1.35%, substantially higher than the median of 0.52%, indicating a positively skewed dataset driven by a few firms with high levels of RSI elevating the mean significantly. Several anomaly variables exhibit a similar pattern, highlighted by significant differences between the mean and median.

4 Methodology and Research Design

In order to test our hypotheses, we make a series of statistical tests. For these, we mainly employ two statistical methods. First, we use Fama and MacBeth (1973) regressions to test the connection between the abnormal returns of short sellers and our explanatory variables. Second, we use a portfolio sorting method in which we analyze returns for portfolios sorted on both RSI and our explanatory variables. In the next subsection (4.1), we explain in greater detail how these portfolios are constructed. In the following subsections (4.2 and 4.3), the methodological approach, connection to our hypothesis, and expected results for our tests are outlined.

4.1 Portfolio and variable construction

4.1.1 Constructing portfolios for RSI and anomalies

After having excluded all firm-month observations with missing Relative Short Interest, we construct RSI quintile portfolios. These portfolios are rebalanced monthly. The short (long) leg of RSI is the portfolio with the highest (lowest) level of Relative Short Interest. Moreover, we create quintile portfolios for all 11 anomalies discussed in Section 3.4, also rebalanced monthly. The anomalies expected by the literature to predict higher future stock returns include Book-to-Market (BM), Momentum (MOM), Gross Profitability Premium (GPP), and Return on Assets (ROA). For these anomalies, the short (long) leg is reflected through lower (higher) values. Anomalies expected to have a negative effect on future returns include Ohlson's O-Score ($O\text{-}Score$), Net Stock Issues (NS), Composite Equity Issues (CEI), Total Accruals ($TACC$), Net Operating Assets (NOA), Asset Growth (AG), and Investments-to-Assets (ITA). For these anomalies, the short (long) leg is reflected through higher (lower) values.

Table 3: Stock market anomalies and their directional indication of future returns

Anomaly	**Abbreviation**	**Predictive direction**
1. Book-to-Market	*BM*	Positive
2. Ohlson's O-Score	*O-Score*	Negative
3. Net Stock Issues	*NSI*	Negative
4. Composite Equity Issues	*CEI*	Negative
5. Total Accruals	*TACC*	Negative
6. Net Operating Assets	*NOA*	Negative
7. Momentum	*MOM*	Positive
8. Gross Profitability Premium	*GPP*	Positive
9. Asset Growth	*AG*	Negative
10. Return on Assets	*ROA*	Positive
11. Investments-to-Assets	*ITA*	Negative

4.1.2 Constructing a composite measure of anomalies and the PERC portfolios

Following the methodology of Wu and Zhang (2019), we construct a composite measure of market anomalies to be able to measure how market anomalies are influenced by short selling, referred to as *PERC*. In constructing the variable *PERC*, we start by assigning each anomaly's quintile portfolio a rank from 1 to 5, taking the predictive direction of each anomaly into account so that 1 is the short leg and 5 is the long leg (see Table 3). Following this, each firm-month receives a value based on the average of all non-missing anomalies' quintile portfolio ranks, giving us the continuous *PERC* variable[6]. Higher (lower) values of this variable represents more positive (negative) anomaly signals. We also construct monthly rebalanced *PERC* quintile portfolios, with the short (long) leg portfolios representing the firms with the lowest (highest) *PERC* values.

4.1.3 Creating portfolios based on earnings announcements

In order to test short sellers' trading reactions to earnings announcements, we sort firm-month observations based on an announcement month dummy variable, assigned the value of 1 for months with earnings announcements and 0 for months without. Earnings

[6]The approach of averaging non-missing anomaly ranks, following Wu and Zhang (2019), reduces the loss of observations and is appropriate given the similar return-predictive characteristics among several of the anomalies.

announcement months are identified using earnings announcements dates data[7]. Additionally, we create dummy variables for positive and negative earnings announcements based on the announcement day return. The negative (positive) announcement dummy variable equals 1 when an earnings announcement occurs and a firm's announcement day return is in the bottom (top) quintile of all returns in the sample on the given day and 0 otherwise.

We then create monthly rebalanced portfolios, distinguishing between months with and without earnings announcements. Our methodology follows Engelberg et al. (2012), who analyze short sellers' reactions to various news events, including earnings announcement news, using daily RSI data. However, without access to daily RSI data, we replicate their approach with monthly data. Aggregating the daily earnings announcement dummies to a monthly basis is feasible due to the quarterly reporting of results on Nordic stock markets, resulting in at most one earnings announcement per firm per month. The specific details of the tests based on these portfolios are discussed in Section 4.3.2.

4.2 Anomaly exploitation and short sellers' abnormal returns

4.2.1 Testing how stock returns relate to RSI and anomalies

The negative relationship between RSI and monthly stock returns is widely documented by related literature and implies that short sellers are informed traders (Desai et al., 2002; Figlewski, 1981; Aitken et al., 1998; Diether et al., 2009). We test this relationship by comparing monthly average returns of the long and short leg portfolios of RSI, as well as analyzing the average returns of a long-short hedge portfolio. Additionally, CAPM alphas are computed for these portfolios to ensure that abnormal performance persists when adjusting for market risk. In all tests, portfolio returns and CAPM alphas are calculated in month $t+1$ based on the sorting of RSI observed in month t, following Wu and Zhang (2019). A CAPM alpha that is significantly lower for the short leg of RSI than for the long leg would be indicative of a negative RSI-return relationship, reinforcing the findings of existing literature.

To test the existence of the 11 anomalies, we calculate average monthly returns and CAPM alphas in month $t+1$ for the short, long, and long-short hedge portfolios for each of the anomalies. The anomalies are defined in Section 4.1.1. Furthermore, the same analysis is made for the portfolios sorted on the composite anomaly signal, *PERC*,

[7]This dataset is more limited than our broader dataset due to limited data availability on earnings announcement dates. Also, we have excluded firms with fewer than 8 reported earnings announcement dates to minimize data noise, further reducing the size of the dataset.

described in greater detail in Section 4.1.2. In line with the literature, we expect the hedge portfolios to generate a positive alpha, implying that a trading strategy based on the anomalies could generate abnormal returns. Table 4 reports results for RSI and *PERC* and Table 13 in the Appendix A.1 reports the results for the each of the anomalies.

4.2.2 Testing the extent to which short sellers target firms on the short and long leg of anomalies

As a first test to examine whether short sellers exploit anomalies, we analyze the time-series average of RSI for the short and long leg portfolios of the selected anomalies and *PERC*. Each row in Table 5 represents portfolios sorted based on its respective anomaly. If exploitation of anomalies accounts for a significant share of short sellers' abnormal return, one would expect to see an overlap between the short leg of RSI with the short leg of anomalies. This would mean that the companies with the highest short interest would also be the companies that display the strongest negative anomaly signals. We also test the difference between the long and short leg portfolios. If this difference is negative and significantly different from zero, it indicates that short sellers target anomalies on the short leg. Table 5 presents the results of this analysis.

4.2.3 Testing the role of short sale constraints in explaining short sellers' abnormal returns

To gain further depth in the analysis on the extent to which short sellers actively exploit anomalies, we report average levels of RSI for the short and long leg of *PERC* in the cross-section of short sale constraints. Asquith et al. (2005) reports a positive relationship between firm size and short interest, suggesting that larger firms are less constrained for short selling. Similarly, Boehme et al. (2006) use illiquidity as a proxy for short sale constraints, with higher illiquidity indicating greater difficulty in executing short sales. Accordingly, we sort firm-month observations into terciles based on *MCAP* and *ILLIQ*, respectively. Within each tercile, we calculate average RSI for the short leg, long leg, and the long-short hedge portfolio formed on *PERC*. If short sellers systematically exploit anomaly signals, we expect the difference of RSI levels between the short and long legs to be more positive and statistically significant among firms facing fewer short sale constraints. Table 6 reports the results of this analysis.

4.2.4 Testing anomaly exploitation through double-sorting portfolio methodology

To further investigate the relationship between short selling and anomaly signals, we adopt an intuitive approach by focusing on the return performance of the extreme portfolios of both RSI and *PERC*. Following Wu and Zhang (2019), we employ a double-sorting portfolio methodology in which firm-months are sorted into 25 sublets based on RSI and *PERC* quintile portfolios. "Overlapping" short leg (long leg) portfolios are the double-sorted portfolios for which both RSI and *PERC* are on the short leg (long leg). The non-overlapping portfolios are double-sorted based on the short (long) leg of RSI and the remaining four quintile portfolios of *PERC* that are not on the short (long) leg.

A result showing that short sellers on the short leg of RSI generate greater negative alpha on the short leg of *PERC* (overlapping) than in other *PERC* portfolios (non-overlapping) would provide support for Hypothesis 1. This would imply that short sellers generate part of their abnormal return by exploiting the most extreme cases of anomaly signals. Table 7 reports the results of this analysis. Moreover, in Table 14 in Appendix A.2, raw returns and CAPM alphas are presented for the for the 25 double-sorted portfolios based on RSI and *PERC*.

4.2.5 Testing anomaly exploitation through time series Fama-MacBeth regressions

To further investigate whether the informational advantage of short sellers is driven by anomaly exploitation, we run a time-series Fama-MacBeth regression with excess stock returns as the dependent variable. The independent variables are RSI, the composite measure of anomaly signals (*PERC*, standardized between 0 and 1)[8], their interaction term, and the market risk premium (MRP)[9]. The underlying equations are shown below in Model 1, Model 2, and Model 3.

$$\begin{aligned} R_{i,t+1} - R_{f,t+1} = \alpha + \beta_1 \mathrm{RSI}_{i,t} + \beta_2 (R_{m,t+1} - R_{f,t+1}) \\ + \beta_3 \log(\mathrm{MCAP}_t) + \beta_4 \log(\mathrm{ILLIQ}_t) + \epsilon_{i,t} \end{aligned} \qquad \text{(Model 1)}$$

[8]The *PERC* variable represent the composite measure of anomalies, as described in Section 4.1.2. Higher (lower) values of *PERC* predict higher (lower) future returns based on literature (see Section 3.4).

[9]Defined as $R_m - R_f$, the excess return of the market portfolio over the risk-free rate.

$$R_{i,t+1} - R_{f,t+1} = \alpha + \beta_1 \text{RSI}_{i,t} + \beta_2 \text{PERC}_{i,t-1} + \beta_3 (R_{m,t+1} - R_{f,t+1}) + \beta_4 \log(\text{MCAP}_t) + \beta_5 \log(\text{ILLIQ}_t) + \epsilon_{i,t} \quad \text{(Model 2)}$$

$$R_{i,t+1} - R_{f,t+1} = \alpha + \beta_1 \text{RSI}_{i,t} + \beta_2 \text{PERC}_{i,t-1} + \beta_3 (\text{RSI}_{i,t} \times \text{PERC}_{i,t-1}) + \beta_4 (R_{m,t+1} - R_{f,t+1}) + \beta_5 \log(\text{MCAP}_t) + \beta_6 \log(\text{ILLIQ}_t) + \epsilon_{i,t} \quad \text{(Model 3)}$$

A lower (higher) value of *PERC* represents the short (long) leg of anomalies. Thus, we expect a negative coefficient on the interaction term between *PERC* and RSI if short sellers generate returns by concentrating their activity in stocks on the short leg of anomalies. Moreover, the previously discussed proxies for short sale constraints, *MCAP* and *ILLIQ*, are used as control variables.

Next, we extend the analysis by regressing RSI directly on the standardized *PERC* variable as the primary independent variable of interest[10]. This test enhances robustness by offering a more direct assessment of the extent to which short sellers target (avoid) stocks with negative (positive) anomaly signals. As previously noted, since lower (higher) *PERC* values correspond to the short (long) leg of anomalies, a negative coefficient on *PERC* would be consistent with short sellers exploiting mispricing captured by anomaly signals. Additionally, the coefficients on *MCAP* and *ILLIQ* are of interest, given the mixed empirical findings on the role of short sale constraints in explaining short sellers' abnormal returns.

$$RSI_{i,t} = \alpha + \beta_1 PERC_{i,t-1} + \beta_2 \log(MCAP_{i,t}) + \beta_3 \log(ILLIQ_{i,t}) + \epsilon_i \quad \text{(Model 4)}$$

To relate the findings from Model 4 to the return predictiveness of RSI, we compare raw returns and CAPM alphas of portfolios sorted on raw RSI (same as those reported in Table 4) to the raw returns and CAPM alphas of portfolios sorted on the residual RSI not explained by Model 4[11]. To do so, we form monthly rebalanced quintile portfolios based on residual RSI and analyze their returns. This approach allows us to assess whether the return predictability of RSI is primarily driven by the information captured in known

[10]The *PERC* variable represents the composite measure of anomalies, as described in Section 4.1.2. Higher (lower) values of *PERC* predict higher (lower) future returns based on prior literature (see Section 3.4).

[11]RSI residuals are the regression residuals of RSI from the Fama-MacBeth regression in Model 4.

anomalies or whether it reflects additional information, as captured by the residuals of the regressions. If the negative RSI-return relationship is largely explained by the independent variables in the Fama-MacBeth model, we would expect the raw returns and CAPM alphas to be substantially reduced when sorting on RSI residuals.

Recognizing that residual RSI and predicted RSI are mechanically linked, we also report the portfolios returns of a double-sorting procedure aimed to isolate all impact of anomaly signals. Specifically, firms are first sorted into quintiles based on predicted RSI, and within each predicted RSI quintile, they are sorted into quintiles based on residual RSI. Returns are then averaged across predicted RSI quintiles for each residual RSI portfolio. The double-sorting procedure enables comparisons across residual RSI portfolios within groups of firms that share similar predicted RSI levels, thereby controlling for any variation driven by anomaly-related information that may persist due to the mechanical link between residual and predicted RSI. As for the portfolios based on residual RSI, we would expect this sorting to generate lower returns and CAPM alphas, compared to the sorting on raw RSI, if the negative RSI-return relationship can be largely explained by anomalies.

4.3 Anticipation of and reaction to earnings events and short sellers' abnormal returns

In multiple statistical tests, we evaluate our second and third hypotheses relating to whether short sellers' trading behavior around earnings announcement news explains some of their abnormal returns. These tests are divided into two parts. In the first part, described in Section 4.3.1, we focus on short sellers' ability to *anticipate* earnings announcement news and position themselves in stocks that will have negative earnings surprises. The second part, presented in Section 4.3.2 is about their ability to *react to* earnings announcement news. In both parts, we perform the tests separately using both raw RSI and the residual RSI from Model 4, with the aim of understanding whether the results persists after controlling for the portion of RSI explained by the 11 anomalies.

4.3.1 Testing to what extent short sellers predict earnings surprises

Firstly, we test our second hypothesis by examining whether the negative relationship between RSI and returns can be explained by short sellers' ability to anticipate future earnings. Previous studies, such as the ones by Guo and Wu (2019), Boehmer et al. (2020), and Engelberg et al. (2012), suggest that such an ability may stem from either possession of private information or superior processing of public information. Following the approach of Wu and Zhang (2019), we conduct three Fama-MacBeth regressions to

test whether short sellers are able to predict future earnings surprises, and whether this ability is related to the exploitation of market anomalies, proxied by the standardized *PERC* variable.

Following Wu and Zhang (2019), Earnings Surprises are measured using the variable *Standardized Unexpected Earnings (SUE)*, defined as the year-over-year change in the EPS released during a 3-month period starting from $t+1$ for the closest quarter, scaled by the stock price in the same month.

$$SUE = \alpha + \beta_1 RSI_t + \beta_2 \log(MCAP_t) + \beta_3 \log(ILLIQ_t) + \varepsilon_t \quad \text{(Model 5)}$$

$$SUE = \alpha + \beta_1 RSI_t + \beta_2 PERC_{t-1} + \beta_3 \log(MCAP_t) + \beta_4 \log(ILLIQ_t) + \varepsilon_t \quad \text{(Model 6)}$$

$$\begin{aligned} SUE = \alpha &+ \beta_1 RSI_t + \beta_2 PERC_{t-1} + \beta_3 (PERC_{t-1} \times RSI_t) \\ &+ \beta_4 \log(MCAP_t) + \beta_5 \log(ILLIQ_t) + \varepsilon_t \end{aligned} \quad \text{(Model 7)}$$

In Model 5, we test whether RSI has predictive power for future earnings surprises, i.e, to what extent short sellers anticipate earnings surprises and position themselves accordingly. Since a positive (negative) *SUE* represents a positive (negative) earnings surprise, we expect a negative coefficient on RSI, suggesting that short sellers avoid stocks with upcoming positive surprises and target those with negative surprises. In Model 6 and Model 7, we control for *PERC* and an interaction variable between *PERC* and RSI, respectively. The purpose of these two regressions is to test the robustness of the relationship between RSI and earnings surprises and to examine whether the predictive power of RSI varies with the level of *PERC*. In these two regressions, *PERC* is standardized between 0 and 1. As mentioned above, we regress each model using both raw RSI and residual RSI (from Model 4).

4.3.2 Testing whether superior reactions to earnings announcements explain a part of short sellers' abnormal returns

In examining our third hypothesis relating to short sellers' reactions to news events, we conduct a series of Fama-MacBeth regressions with methodological inspiration from

Engelberg et al. (2012). Specifically, we assess whether part of short sellers' abnormal profits is generated after earnings announcement news. Unlike Engelberg et al. (2012), who use daily shorting volume and calculate 20-day returns from the exact earnings announcement day, we replicate their approach using monthly RSI. For each month, the earnings announcement (EA) dummy is based on whether an earnings announcement has occurred in that month or not. These regressions are conducted on the more narrow dataset with non-missing earnings announcement dates.[12] We regress these models using both raw RSI and the RSI residuals obtained from Model 4, with the latter included to test the informativeness of RSI once the effect of the anomalies is excluded. The underlying statistical models are shown below.

$$R_{i,t+1} - R_{f,t+1} = \alpha + \beta_1 \left(R_{m,t+1} - R_{f,t+1}\right) + \beta_2 RSI_{i,t} + \epsilon_{i,t+1} \tag{Model 8}$$

$$\begin{aligned} R_{i,t+1} - R_{f,t+1} = \alpha + \beta_1 \left(R_{m,t+1} - R_{f,t+1}\right) + \beta_2 RSI_{i,t} + \beta_4 EA_{i,t} \\ + \beta_5 (EA_{i,t} \times RSI_{i,t}) + \epsilon_{i,t+1} \end{aligned} \tag{Model 9}$$

$$\begin{aligned} R_{i,t+1} - R_{f,t+1} = \alpha + \beta_1 \left(R_{m,t+1} - R_{f,t+1}\right) + \beta_2 RSI_{i,t} + \beta_3 PosEA_{i,t} \\ + \beta_4 NegEA_{i,t} + \beta_5 (PosEA_{i,t} \times RSI_{i,t}) \\ + \beta_6 (NegEA_{i,t} \times RSI_{i,t}) + \epsilon_{i,t+1} \end{aligned} \tag{Model 10}$$

The baseline Model 8 tests the relationship between stock returns and RSI, while controlling for the Market Risk Premium. In Model 9 we add an earnings announcement news dummy as well as an interaction term with RSI. This is to examine whether short sellers' trading behavior after earnings announcements explains part of the negative RSI-return relationship documented by literature, suggesting superior processing of public information. Following Engelberg et al. (2012), Model 10 adds dummy variables and interaction terms for negative and positive earnings announcements. This is to further understand whether short sellers exploit certain types of news. The EA dummy is negative (positive) if the one-day return at the earnings announcement date is in the bottom (top) quintile of the returns on that day. For Model 9 and Model 10, a negative coefficient on the interaction terms would indicate that higher levels of RSI during months with earnings announcements predict lower subsequent returns, i.e., providing support for our third hypothesis that short sellers generate abnormal returns by reacting efficiently to earnings announcements. Table 11 reports the results of this analysis.

[12] All firms without any reported earnings announcement dates are excluded. Additionally, to reduce data noise, we exclude all firm-month observations from firms that report earnings for less than half of the available earnings announcement dates over the 5-year period.

To further investigate our third hypothesis, we calculate raw returns and CAPM alphas for portfolios double-sorted on RSI quintiles and the Earnings Announcement (EA) dummy. Firm-month observations are sorted into 10 different portfolios based on the RSI quintile and the EA dummy. This allows us to assess whether abnormal next-month returns and CAPM alphas generated by short sellers on the short leg of RSI are particularly prevalent for firms that have reported earnings. Moreover, we also compute next-month returns and alphas for the RSI long - short hedge portfolio. Furthermore, to understand the explanatory power of the direction of the earnings announcement, the same methodology is employed for negative and positive EAs.[13] A result showing statistically significant negative alpha for a double-sorted portfolio on the short leg of RSI and with a EA news event would provide support for hypothesis 3, indicating that abnormal returns are generated in connection to earnings announcements. In Table 12, we report the returns based on this analysis for the short leg, long leg, and long - short hedge portfolios of RSI.

[13]The EA dummy is negative (positive) if the one-day return at the earnings announcement date is in the bottom (top) quintile of the returns on that day. The definition is the same as the one used in the Model 10 Fama-MacBeth regression.

5 Empirical Findings

5.1 The role of anomalies in explaining short sellers' abnormal returns

5.1.1 Raw returns and CAPM alphas for RSI and PERC

Table 4: Raw returns and CAPM alphas for RSI and *PERC* quintiles (see Section 4.2.1 for methodology)

	Panel A: Raw Returns		
	Long	**Short**	**Long-Short**
RSI	1.08***	0.60***	0.48
PERC	1.12*	-1.13	2.26**
	Panel B: CAPM Alphas		
	Long	**Short**	**Long-Short**
RSI	-0.16	-0.78***	0.62
PERC	0.29	-2.45***	2.74***

Note: This table presents raw returns (Panel A) and CAPM alphas (Panel B) for quintile portfolios sorted on RSI and *PERC*, the composite measure of anomalies. The short (long) leg portfolio for RSI has the highest (lowest) level of RSI. For *PERC*, the short (long) leg is the quintile portfolio predicted by literature to yield the lowest (highest) subsequent return. T-statistics are adjusted for heteroskedasticity and autocorrelation in line with Newey and West (1987). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

The results presented in Table 4 provide support for the observed negative relationship between short selling and stock returns documented by a large branch of finance literature (Desai et al., 2002; Figlewski, 1981; Aitken et al., 1998; Diether et al., 2009). This is indicated by the statistically significant CAPM alpha of -0.78% of the short leg portfolio of RSI. While the CAPM alpha for the long-short portfolio is not significant, it is directionally positive, in line with expectations. All in all, these findings provide indicative support for the presence of a negative RSI-return relationship on the short leg of RSI.

As discussed in Section 4.1, quintile portfolios based on anomalies are constructed so that the short (long) leg is predicted by literature to have a negative (positive) effect on stock returns (see Section 3.4 for references on the individual anomalies). Given this, the results shown in Table 13 in the Appendix are largely in line with expectations, indicating that trading strategies based on six of the eleven included anomalies generate a positive alpha for the long - short hedge portfolios. Moreover, the quintile portfolios constructed based on the composite measure of anomalies, *PERC*, display a similar pattern with a significant and positive average return of 2.26% and a CAPM alpha of 2.74% for the long-short portfolio. Hence, the results in Tables 4 and 13 indicate not only that publicly available anomalies are available in our dataset, they also imply that *PERC* portfolios successfully capture anomaly signals. These initial results find support for the negative RSI-return relationship, the existence of anomalies in our dataset, and using the *PERC*

variable as a proxy for the equally weighted average of the trading signals provided by the 11 anomalies. This provides an encouraging backdrop against which to continue our investigation into the explanation for the abnormal returns generated by short sellers.

5.1.2 RSI by market anomalies

Table 5: Average RSI for long, short, and long-short portfolios based on market anomalies (see Section 4.2.2 for methodology)

	Long	**Short**	**Long-Short**
BM	1.44	1.29	0.15
MOM	0.97	1.44	-0.47***
O-Score	1.81	1.30	0.52***
NSI	1.98	1.00	0.98***
CEI	1.89	1.01	0.88***
TACC	1.54	1.78	-0.24
NOA	1.69	1.80	-0.10
GPP	1.42	1.10	0.32***
AG	1.21	1.57	-0.36**
ROA	1.52	0.81	0.71***
ITA	1.42	1.80	-0.38**
PERC	1.38	0.97	0.41***

Note: This table reports the time-series average of portfolio RSI for the short leg, long leg, and long - short hedge portfolio for each of the 11 anomalies, as well as the *PERC* variable. The short (long) legs of anomalies are the quintile portfolios predicted by literature to yield the lowest (highest) subsequent return. T-statistics are adjusted for heteroskedasticity and autocorrelation in line with Newey and West (1987). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

Table 5 shows average time-series levels of Relative Short Interest based on each anomaly's long and short leg portfolios, as well as the long - short hedge portfolio. The results show that the levels of RSI are on average greater for firms on the long leg of anomalies than on the short leg, illustrated by positive and statistically significant positive RSI levels for several of the long - short hedge portfolios. Three anomalies, *MOM*, *AG* and *ITA*, are exceptions from this rule and display differences in RSI levels between the long and short leg portfolios that are negative and significantly different from zero. However, as the corresponding result for *PERC*, the composite measure of anomalies, is also positive, we interpret this result as short sellers generally being more present in firms on the long leg of anomalies. Although this, at a first glance, contradicts the hypothesis of short sellers active use of anomalies in generating returns, one possible explanation for the finding, further supported by the results presented in the next Section 5.1.3, is the apparent presence of short sale constraints in our dataset.

Table 6: Evaluation of the effect of short sale constraints on average levels of RSI (See Section 4.2.3 for methodology)

Panel A: Average measure of short sale constraints: Market Cap and Illiquidity

	Long	**Short**	**Long-Short**
MCAP	3,792***	339***	3,452***
ILLIQ	0.32***	0.39***	-0.07***

Panel B: Average RSI sorted on *PERC* by short sale constraints

	Long	**Short**	**Long-Short**
Market Cap			
Small	0.41***	0.51***	-0.09***
Large	1.88***	3.03***	-1.15***
Large - Small	1.46***	2.52***	-1.05***
Illiquidity			
Low	2.19***	2.22***	-0.04
High	0.82***	0.47***	0.36***
High - Low	-1.36***	-1.76***	0.39***

Note: This table reports short sale constraints, using the proxies market capitalization (*MCAP*) and (*ILLIQ*). Panel A reports average scores on *MCAP* (in EUR) and *ILLIQ* (using the method of Amihud (2002)) for the short leg, long leg, and long - short hedge portfolios of *PERC*. In Panel B, the two measures of short sale constraints, *MCAP* and *ILLIQ*, are sorted into tercile portfolios. For each tercile portfolio, we use Fama and MacBeth (1973) to compute the average RSI for the long and short legs of *PERC*. T-statistics are adjusted for heteroskedasticity and autocorrelation in line with Newey and West (1987). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

5.1.3 The role of short sale constraints

As discussed in Section 2.2 of the Literature Review, the existence of short sale constraints is found by several studies to be closely related to that of anomalies (Wu and Zhang, 2019; Stambaugh et al., 2012). In Panel A of Table 6, we find support for this in our dataset. The table reports the time-series average market capitalization (*MCAP*) and illiquidity score (*ILLIQ*) for the long leg, short leg, and long - short leg hedge portfolios for *PERC*. We find a statistically significant positive *MCAP* and a statistically significant negative *ILLIQ* for the long - short hedge portfolios, indicating that short sale constraints are more prevalent on the short leg of anomalies than on the long leg. This result, providing support to the aforementioned studies, also relates to Miller (1977), who argues that short sale constraints give rise to mispricing.

Panel B of Table 6 displays average RSI, calculated using Fama and MacBeth (1973), for a series of double-sorted portfolios sorted on *PERC* quintile portfolios and tercile portfolios based on *MCAP* and *ILLIQ*, respectively. Across the various *PERC* portfolios, we find that short selling is more common in large and less illiquid stocks, signaling the appropriateness of using *MCAP* and *ILLIQ* as proxies for short sale constraints. Turning our focus to the effect of *PERC*, i.e., the extent to which anomaly signals influence short selling decisions under the influence of short sale constraints, we find conflicting results.

In line with Wu and Zhang (2019), the average RSI for the long - short *PERC* portfolio for firms with larger *MCAP* is greater than for firms with smaller *MCAP*, implying that anomaly exploitation is more prevalent among less short sale constrained firms. However, for portfolios double-sorted on *PERC* and *ILLIQ*, the same pattern is not observed. Unlike Wu and Zhang (2019), who find that short sellers are more present on the short leg of *PERC* for stocks with less illiquidity (less short-sale-constrained), our results are inconclusive, possibly due to the existence of constrained liquidity across the sample.

Seen in the broader perspective of this paper, these results provide evidence of the existence of short sale constraints in our dataset. Furthermore, short sale constraints are more prevalent among firms with stronger negative anomaly signals. Regarding the extent to which short sale constraints influence the level of anomaly exploitation among short sellers, our results are inconclusive and vary with our two short sale constraint proxies.

5.1.4 Evaluating portfolio returns based on RSI and PERC with a double-sorting portfolio methodology

Table 7 presents the results for portfolios single-sorted on RSI (columns 1 and 3) and double-sorted on RSI and *PERC*, the composite measure of anomalies, (columns 2 and 4). The raw returns and CAPM alphas for the single-sorted RSI portfolios, also presented in Table 4, provide a useful benchmark against which the returns of the double-sorted portfolios can be analyzed. The double-sorted overlapping portfolio simultaneously on the short leg of RSI and *PERC*, yields a negative and significant CAPM alpha of 2.03%, significantly higher than the negative 0.78% alpha for the single-sorted short leg of RSI. The higher abnormal return generated by the overlapping short leg portfolio relative to the single-sorted high RSI portfolio signals that the negative RSI-return relationship is more concentrated in firms that display stronger anomaly signals. This finding, consistent with Wu and Zhang (2019), provides support for our first hypothesis that short sellers earn abnormal returns by exploiting publicly observable anomalies. However, since the alpha for non-overlapping firms on the short leg of RSI is still negative and significant, a meaningful part of the negative RSI-return relationship appears to be explained by other factors than anomaly exploitation.

In table 14 in appendix A.2, we report the raw returns and CAPM alphas for 25 sub-portfolios based on the 5 x 5 double-sorted portfolios sorted on RSI and *PERC* quintiles. This table provides additional insight to the analysis solely focusing on the overlapping portfolios in the above paragraph. The double-sorted portfolios on the short leg of *PERC* and second- and third-highest RSI quintiles generate negative and significant alphas of

Table 7: Double-sorted portfolios sorted on RSI and *PERC* quintiles (see Section 4.2.4 for methodology)

	Raw Return		**CAPM Alpha**	
	(1)	(2)	(3)	(4)
		PERC		PERC
High RSI (Short)	0.60***		-0.78***	
Overlapping (*PERC* Short Leg)		-0.45		-2.03*
Nobs		*365*		*365*
Non-Overlapping (*PERC* remaining)		0.76***		-0.58**
Nobs		*2,710*		*2,710*
Difference		-1.21		-1.44
Low RSI (Long)	1.08***		-0.16	
Overlapping (*PERC* Long Leg)		1.38***		0.30
Nobs		*734*		*734*
Non-Overlapping (*PERC* remaining)		0.91**		-0.38
Nobs		*2,663*		*2,663*
Difference		0.47		0.68
Long - Short	0.48		0.62	
Overlapping		1.83		2.32*
Non-Overlapping		0.15		0.20
Difference		1.68		2.12

Note: This table reports portfolio returns for double-sorted portfolios. Columns 2 and 4 report returns for overlapping and non-overlapping returns based on RSI and *PERC*. Firm-month observations in overlapping portfolios are simultaneously on the short (long) leg of RSI and *PERC*. Non-overlapping firms are the remaining firm-month observations within the short (long) leg of RSI. Moreover, we report the difference between returns for overlapping and non-overlapping firms for the short leg, long leg, and long - short leg of RSI portfolios. For reference, columns 1 and 3 report the returns from single-sorted RSI portfolios presented in Table 4. T-statistics are adjusted for heteroskedasticity and autocorrelation in line with Newey and West (1987). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

4.47% and 2.76%, respectively. This indicates a higher degree of anomaly exploitation in the RSI quintile portfolios slightly below the short leg of RSI. One possible explanation for this result, tied to the results observed in Table 6 in Section 5.1.3, is that our dataset contains short sale constraints. In fact, Figlewski (1981) uses the level of RSI itself as a proxy for short sale constraints, arguing that unobserved demand for shorting is greater in the most shorted stocks. If high levels of RSI are indicative of short sale constraints, one would expect anomaly exploitation, encouraged by less short sale constraints, to be more prevalent in the second- and third-highest RSI quintile portfolios than on the short leg of RSI. This analysis, while still consistent with our first hypothesis that short sellers generate abnormal returns through anomaly exploitation, implies that this exploitation is more apparent for slightly less shorted firms, since these are inherently subject to fewer short sale constraints.

5.1.5 Fama Macbeth regressions on excess return and RSI

Table 8: Fama-MacBeth regressions on return, testing the explanatory power of RSI and *PERC* (see Section 4.2.5 for methodology)

	Model 1	**Model 2**	**Model 3**
MRP	0.24	0.23	0.19
	(0.46)	(0.46)	(0.37)
RSI	-0.00	-0.00	-0.00
	(-0.75)	(-0.63)	(-1.57)
PERC		0.03***	0.03***
		(3.25)	(3.72)
RSI × PERC			-0.00
			(-1.29)
Log (MCAP)	0.00**	0.00*	0.00*
	(2.53)	(1.78)	(1.66)
Log (ILLIQ)	0.00	0.00	0.00
	(1.38)	(0.92)	(0.91)
Intercept	0.03	0.05	0.05
	(0.62)	(1.14)	(1.32)
Avg. Nobs	273	273	273
Avg. R^2 (%)	4.16	5.12	5.46

Note: This table reports coefficients from Fama-MacBeth regressions of stock returns on RSI, *PERC*, and their interaction term. The market risk premium (MRP) is included to control for market risk (see Section 4.2.3 for further details). Log (*MCAP*) and log (*ILLIQ*) are included as control variables for short sale constraints. The underlying equations Model 1, Model 2, and Model 3 are presented in Section 4.2.5. T-statistics, reported in parentheses, are adjusted for heteroskedasticity and autocorrelation in line with Newey and West (1987). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

While the portfolio analysis in the previous section highlights the role of short sellers in anomaly exploitation, it does not fully capture how short interest predicts returns across all stocks. To address this, we complement the portfolio results with Fama-MacBeth regressions that test whether RSI predicts future returns after controlling for risk factors and anomaly signals. Firstly, we estimate a series of time-series Fama-MacBeth regressions using next-month excess stock returns as the dependent variable and RSI and the composite measure of anomalies, *PERC*, as the independent variables. In the first specification, we regress excess returns on RSI only, controlling for the market risk premium (*MRP*), and the two proxies for short sale constraints, firm size (*MCAP*) and illiquidity (*ILLIQ*).

The coefficient on RSI is negative, as expected, but statistically insignificant. This may be due to the return predictiveness of short interest being concentrated in the most shorted stocks, those on the short leg, rather than being uniformly distributed across all stocks. This lends further justification for the portfolio sorting methodology used in Section 5.1.4, which allows the investigation to focus on the short and long leg of RSI separately. The statistical insignificance of RSI in explaining the cross-section of returns is also aligned with what we find in Table 4, where no significance is found for the next-month CAMP

alpha of the long leg (-0.16), while it is highly significant for the short leg (-0.78***). If the predictiveness of short interest is concentrated in the short leg, a Fama and MacBeth (1973) regression that averages across all stocks might fail to uncover the informativeness of RSI.

To test whether anomaly signals themselves are predictive of future returns, the second specification includes the composite measure of anomalies, *PERC*, as an additional regressor. The coefficient on *PERC* is positive and statistically significant, indicating that stocks with stronger negative anomaly signals, those with lower *PERC*, tend to yield lower future returns. This finding is consistent with a well-established body of literature, as discussed in Section 3.4, which supports the notion that anomaly signals are informative and capture predictable mispricing across stocks in the cross-section of returns.

To more rigorously examine whether short sellers exploit this anomaly-related information, the third specification includes an interaction term between RSI and *PERC*. The negative coefficient on this interaction term indicates that, conditional on a given level of short interest, a shift from the long leg toward the short leg of anomalies strengthens the negative relationship between RSI and subsequent one-month returns. This finding is directionally consistent with the notion that short interest is more predictive of poor future performance when anomaly signals are strongly negative. However, the interaction term is not statistically significant, which limits definitive conclusions regarding systematic targeting of these stocks by short sellers. The coefficient on RSI itself becomes more negative in this specification (t = –1.57, close to the 10% threshold), potentially reflecting an enhanced predictive role for short interest in the presence of anomaly signals, although this estimate also falls short of standard significance thresholds.

Although not conclusive, these results offer tentative support for our first hypothesis that short sellers exploit anomalies to generate abnormal returns (see Section 2.4), and underscore the value of further investigation into the conditional informativeness of short interest. This motivates the subsequent analysis, in which we regress RSI directly on anomaly signals to examine their relationship more closely. We then analyze the residual component of RSI, controlling for the portion explained by anomalies, to assess whether it contains independent predictive information about future returns.

Panel A of Table 9 presents the results from a Fama-MacBeth regression of Relative Short Interest (RSI) on *PERC*, the composite anomaly measure. We include market capitalization (*MCAP*) and illiquidity (*ILLIQ*) as control variables to account for short sale constraints. The coefficient on *PERC* is negative and statistically significant at the 1% level, indicating that stronger negative anomaly signals (i.e., lower values of *PERC*) are associated with higher levels of short interest. Quantitatively, a one unit increase in

Table 9: Fama-MacBeth regression on RSI, testing the explanatory power of *PERC* (see Section 4.2.5 for methodology)

Panel A: Model 4 Fama-MacBeth regression of RSI on anomalies

	Model 4
PERC	-0.44***
	(-9.46)
Log(MCAP)	0.19***
	(24.60)
Log(ILLIQ)	-0.32***
	(-24.98)
Intercept	-0.70***
	(-16.15)
Avg. Nobs	273
Average R^2	16.22

Panel B: Raw Returns to portfolios sorted on raw and residual RSI

	Long	**Short**	**Long - Short**
Raw RSI	1.01***	0.62***	0.39
Residual RSI	1.07***	0.55***	0.52*
Controlled for predicted RSI	0.92**	0.26***	0.66**

Panel C: CAPM alphas to portfolios sorted on raw and residual RSI

	Long	**Short**	**Long - Short**
Raw RSI	-0.16	-0.78***	0.62
Residual RSI	-0.05	-0.88***	0.83**
Controlled for predicted RSI	-0.24	-1.19***	0.95**

Note: Panel A reports results of the time-series Fama and MacBeth (1973) regression of RSI on *PERC*, the composite measure of anomalies. *PERC* is standardized between 0 and 1. Panels B and C report raw returns and CAPM alphas for portfolios sorted on raw RSI, residual RSI from Model 4, and the residual RSI controlled for predictive RSI (Model 4). T-statistics are adjusted for heteroskedasticity and autocorrelation following Newey and West (1987) and presented in parentheses. *, **, and *** indicate statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.

the standardized *PERC* variable predicts an increase of approximately 0.44 percentage points in RSI, supporting the hypothesis that short sellers actively target stocks with more pronounced negative anomaly signals. These results complement the indicative, though statistically inconclusive, interaction effects observed in the return regressions in Table 8. Our finding is consistent with Wu and Zhang (2019) and extends the existing literature by demonstrating that this relationship also holds in more recent data from Nordic stock markets. Furthermore, the coefficients for the control variables align with expectations, showing that lower short sale constraints (larger market capitalization and lower illiquidity) predict higher levels of RSI.

Building on this, Panels B and C of Table 9 further explore the relationship between RSI and future stock returns by analyzing portfolios sorted on raw and residual RSI measures. The residual RSI reflects the portion of RSI not explained by the anomaly

signals in the Fama and MacBeth (1973) regressions in Model 4. We find that while raw RSI significantly predicts future returns and CAPM alphas, the predictive power becomes even stronger when we focus on the residual component of RSI. Sorting on residual RSI leads to larger long-short return spreads and higher CAPM alphas than sorting on raw RSI, suggesting that short sellers utilize additional information beyond the signals provided by the 11 anomalies. Moreover, when further controlling the residual RSI for predicted RSI through a double-sorting procedure, to account for the mechanical link between raw and residual RSI, the residual RSI continues to exhibit strong return predictability. Interestingly, these findings contrast with those of Wu and Zhang (2019), who find that sorting on residual RSI significantly decreases the alpha. Consequently, our results highlight an important insight in the context of more recent Nordic stock market data: while a substantial portion of the RSI–return relation can be attributed to public anomaly information, a meaningful and economically significant portion remains unexplained.

5.2 The role of earnings events in explaining short sellers' abnormal returns

5.2.1 Earnings surprise anticipation

Following the results in Section 5.1, we aim to understand the portion of RSI, and the RSI-return relationship, that cannot be explained by public anomalies. We begin by examining the predictive power of RSI on earnings surprises, and the extent to which this can be explained by factors beyond anomalies. Table 10 shows the outputs of Fama and MacBeth (1973) regressions on future earnings surprises using RSI, *PERC* (the composite measure of anomalies), and their interaction term, controlling for *MCAP* and *ILLIQ*. Panel A shows the results based on raw RSI, while panel B reports the regressions using the residual RSI (controlled for the effect of the 11 anomalies) of Model 4. In the baseline model, Model 5, regressing standardized unexpected earnings (SUE) on RSI shows that higher (lower) short interest predicts more negative (positive) earnings surprises. Across both panels, RSI consistently exhibits a negative and significant coefficient, indicating that short sellers possess predictive information about future earnings. This finding is consistent with prior studies, including Guo and Wu (2019) and Boehmer et al. (2020), which document short sellers' ability to anticipate firm fundamentals performance, before the release of such information.

In Model 6 we include *PERC* in the regressions and find that it has positive and significant coefficients in both panels, showing that firms with stronger negative (positive) anomaly signals experience more negative (positive) earnings surprises. The limited dif-

Table 10: Fama-MacBeth regressions on future earnings surprises (*SUE*), using raw and residual RSI (see Section 4.3.1 for methodology)

Panel A: Raw RSI

	Model 5	**Model 6**	**Model 7**
Raw RSI	-0.18***	-0.17***	-0.56***
	(-3.82)	(-3.61)	(-5.85)
PERC		0.75***	2.34***
		(2.93)	(4.21)
PERC × RSI			-1.07***
			(-3.83)
Log(*MCAP*)	-0.21***	-0.24***	-0.26***
	(-2.87)	(-3.46)	(-3.65)
Log(*ILLIQ*)	-0.31***	-0.31***	-0.33***
	(-3.79)	(-3.78)	(-3.98)
Intercept	1.14***	1.61***	2.18***
	(2.92)	(4.38)	(4.94)
Avg. Nobs	132	132	132
Avg. R^2 (%)	5.67	6.38	9.99

Panel B: Residual RSI from Model 4 (see Table 9)

	Model 5	**Model 6**	**Model 7**
Residual RSI	-0.17***	-0.17***	-0.53***
	(-3.67)	(-3.61)	(-5.63)
PERC		0.84***	0.47
		(3.30)	(1.49)
PERC × RSI			-1.02***
			(-3.55)
Log(*MCAP*)	-0.24***	-0.28***	-0.30***
	(-3.34)	(-4.06)	(-4.21)
Log(*ILLIQ*)	-0.25***	-0.26***	-0.23**
	(-2.89)	(-2.98)	(-2.75)
Intercept	1.20***	1.74***	1.78***
	(3.09)	(4.79)	(4.68)
Avg. Nobs	132	132	132
Avg. R^2 (%)	5.64	6.38	9.84

Note: This table reports coefficients from Fama and MacBeth (1973) regressions of future earnings surprise (SUE) on RSI in month t, *PERC* in month $t-1$, and their interaction. Control variables include Log(*MCAP*) and Log(*ILLIQ*) in month t, following Wu and Zhang (2019). *SUE* is defined as the EPS announced during a 3-month period beginning in month $t+1$ for the next quarter, minus the EPS announced four quarters ago, scaled by the stock price in month t. T-statistics are adjusted for heteroskedasticity and autocorrelation following Newey and West (1987) and presented in parentheses. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

ference between raw and residual RSI coefficients, however, implies that short sellers' predictive power is not primarily driven by the 11 anomalies. Aligned with this, the coefficient on *PERC* is slightly higher in panel B when using residual RSI, which controls for the component of short interest explained by anomaly signals. The findings regarding anomaly signals in the context of future earnings surprises are consistent with those from the Fama and MacBeth (1973) regressions on RSI shown in Table 9, and offer less support for the conclusion of Wu and Zhang (2019), by suggesting that most of the predictive power of short interest in Nordic stocks is not fully explained by known anomaly signals. However, the negative and significant interaction term between RSI and *PERC* suggests that, for firms with the same level of short interest, a movement from the long leg toward

the short leg of anomalies intensifies the negative relationship between RSI and future earnings surprises. This aligns with previous findings that the predictive power of short interest may be concentrated in stocks that exhibit stronger negative anomaly signals. Taken together, these results indicate that while short selling is related to anomalies, short sellers' anticipatory power also reflects factors beyond the exploitation of these signals. Such additional factors could include superior processing of public information or access to private information. In the subsequent section, we consequently extend the analysis to investigate the relationship between short sellers' returns and the timing of trades following earnings announcements.

5.2.2 Earnings announcements

Table 11: Fama-MacBeth regressions on stock returns around Earnings Announcements (EA) based on raw and residual RSI (see Section 4.3.2 for methodology)

	Raw RSI			**Residual RSI**		
	Model 8	**Model 9**	**Model 10**	**Model 8**	**Model 9**	**Model 10**
MRP_{t+1}	1.24***	1.53***	1.34***	0.86***	1.05***	1.35***
	(2.82)	(2.81)	(3.15)	(2.73)	(2.70)	(2.73)
RSI	-0.09	0.05	0.16	-0.00	0.00	0.00
	(-1.12)	(0.31)	(0.99)	(-1.00)	(0.36)	(0.38)
EA		-0.00			-0.02***	
		(-0.49)			(-3.08)	
Positive EA			0.00			-0.02
			(0.07)			(-1.63)
Negative EA			0.02***			0.00
			(2.33)			(0.19)
RSI $*$ EA		-0.05			-0.01	
		(-0.06)			(-1.02)	
RSI $*$ Pos. EA			0.30			0.00
			(0.27)			(0.39)
RSI $*$ Neg. EA			-1.06***			-0.01***
			(-2.67)			(-2.72)
Intercept	0.02	0.03	0.01	0.01	0.02	0.03
	(0.89)	(1.33)	(0.53)	(0.75)	(1.22)	(1.30)
Avg. Nobs	50	50	50	46	46	46
Average R^2(%)	12.46	8.03	11.56	12.08	12.39	9.70

Note: This table reports time-series Fama and MacBeth (1973) regressions on excess stock returns during $t+1$, with methodological inspiration from Engelberg et al. (2012). Model 8 regresses on RSI and MRP, Model 9 includes an Earnings Announcement (EA) dummy, and Model 10 includes dummies for positive and negative EAs. These models are described in greater detail in Section 4.3.2. Residual RSI represents the RSI residuals not explained by anomalies, from Model 4. T-statistics are adjusted for heteroskedasticity and autocorrelation in line with Newey and West (1987) and presented in parentheses. *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

After showing that both RSI itself and the RSI-return relationship are only partly explained by public anomalies in Section 5.1, and that short sellers' ability to predict future earnings surprises mainly stems from factors beyond simply acting on known anomalies in Section 5.2.1, we now turn to investigate whether better processing of public information could be one such factor. Table 11 shows the results from Fama and MacBeth (1973)

regressions of next-month stock returns on RSI and earnings announcement (EA) dummies, performed with methodological inspiration from Engelberg et al. (2012). Across all three models, we find limited evidence that either raw or residual RSI on its own predicts returns around earnings announcements. However, the interaction between RSI and negative earnings surprises stands out as negative and statistically significant, suggesting that short sellers are especially informed when firms release bad news. This holds even after controlling for public anomaly signals, using the residual RSI from Model 4. Although the overall signal is weak in regressions, the significant interaction effect is interesting enough to warrant further investigation.

Table 12: Raw returns and CAPM alphas for double-sorted portfolios sorted on RSI and Earnings Announcements, EA (see Section 4.3.2 for methodology)

Panel A: Sorted on raw RSI and Earnings Announcement

		Raw Return				**CAPM Alpha**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Type of EA		**All**	**Neg.**	**Pos.**		**All**	**Neg.**	**Pos.**
High RSI (Short)	0.71**				-0.86**			
EA		-2.27*	-3.02**	-3.88**		-3.87***	-4.07***	-4.83**
No EA		1.49	0.70	0.75		-0.14	-0.81	-0.62
Difference		-3.76**	-3.72**	-4.63**		-3.73***	-3.26**	-4.21**
Low RSI (Long)	1.44***				0.16			
EA		-0.20	1.72	0.01		-0.97	1.18	-0.56
No EA		1.32	0.96	1.22		0.08	-0.24	-0.01
Difference		-1.51	0.76	-1.21		-1.05	-1.42	-0.55
Low - High (L-S)	0.73				1.02*			
EA		2.07*	4.74	3.89*		2.90**	5.24***	4.27**
No EA		-0.17	0.26	0.47		0.22	0.57	0.61
Difference		2.24	4.48	3.42		2.68**	4.67**	3.66*

Panel B: Sorted on residual RSI and Earnings Announcement

		Raw Return				**CAPM Alpha**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Type of EA		**All**	**Neg.**	**Pos.**		**All**	**Neg.**	**Pos.**
High RSI (Short)	0.29				-1.56***			
EA		-1.56	-1.91	-2.19		-3.74***	-3.41***	-4.30**
No EA		0.94	0.68	0.63		-1.06	-1.60**	-1.46**
Difference		-2.51	-2.59	-2.81		-2.68**	-1.81	-2.84
Low RSI (Long)	1.33***				0.14			
EA		-0.05	0.16	-0.80		-0.46	-0.10	-1.09
No EA		1.54*	1.26*	1.53*		0.41	0.02	0.24
Difference		-1.59	-1.10	-2.33		-0.87	-0.12	-1.33
Low-High (L-S)	1.04*				1.79***			
EA		1.51	2.08	1.39		3.28***	-3.31***	-3.21*
No EA		0.60	0.58	0.91		1.47	-1.62*	-1.70*
Difference		0.92	1.49	0.48		1.81	1.69	1.51

Note: This table reports next-month portfolio returns for double-sorted portfolios. Results are shown for portfolio sorting based on both raw RSI (Panel A) and residual RSI (Panel B), where residual RSI is computed in the Fama and MacBeth (1973) regression from Section 5.1.5 (see Table 9). Columns 1 and 5 report returns for the short leg, long leg, and long-short hedge portfolios based on RSI alone. Columns 2–4 and 6–8 break down these returns based on whether a firm-month includes an earnings announcement ("EA") or not ("No EA"). "EA" firm-months are those in which an earnings announcement occurs, and are further split into all EAs, negative EAs, or positive EAs. Negative (positive) earnings announcements are defined as those in the bottom (top) quintile of one-day stock returns on the announcement day. "No EA" months are those without an earnings announcements. For each RSI leg (short, long, and long–short), we report the difference in returns between the "EA" and "No EA" subsamples. T-statistics are adjusted for heteroskedasticity and autocorrelation following Newey and West (1987). *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

To dig deeper, we turn to a more intuitive double sorting approach, similar to what we used in Section 5.1.4, to explore whether the RSI–return relationship is more pronounced

around earnings announcements, particularly in the short leg of RSI. Even though the Fama and MacBeth (1973) regressions in Table 11 were mostly inconclusive, we expect that the portfolio sorting methodology could show a stronger effect, since the regression averages across the full cross-section could miss patterns of informativeness that are concentrated in, for example, the most shorted stocks. The results of this analysis is presented in Table 12.

By focusing on the extremes of RSI and examining how they align with earnings news, we may better capture situations where short sellers are particularly well-informed. Following the results of Engelberg et al. (2012), showing that short sellers are skilled at anticipating bad news and earn a return surrounding such announcements, we expect any predictive signal to be more apparent in the short leg of RSI and around earnings announcements. The results are compelling. Table 12 shows a strong connection between earnings announcements and next-month profits generated by short sellers. The overlapping portfolio analysis shows that the predictive power of RSI for next-month CAPM alphas is particularly strong in months when firms announce earnings, suggesting that short sellers derive abnormal returns by reacting to these events. This holds when sorting on both raw and residual RSI (controlled for anomaly signals). For example, the CAPM alpha following earnings announcements months (including *All* earnings announcements, i.e. positive, negative and neutral) for the short leg of RSI is -3.87*** when sorting portfolios on raw RSI and -3.74*** for residual RSI. This is to be compared to the alpha of -0.86*** for a portfolio single sorted on high RSI (the short leg of RSI).[14] Also the difference between the long and short leg of RSI is significant when overlapping with earnings announcements, with the long-short portfolio generating a positive alpha of 2.90** (3.28*** when sorting on residual RSI).

In contrast, there are no significant returns for the long leg of RSI, and the long-short hedge portfolios yield positive and statistically significant CAPM alphas when looking at firm-months with earnings announcements. This implies that the return effect of EA news events is concentrated in the high RSI portfolio, and the performance gap between long and short legs is economically and statistically meaningful. In total, this supports the findings of Engelberg et al. (2012), by showing that part of the negative relation between short sales and future earnings can be attributed to the informed reaction to news releases.

Notably, alphas are even more negative when focusing on positive and negative earnings

[14]The regressions in Table 11 are conducted on a smaller dataset with non-missing earnings announcement dates, see Section 4.3.2 for methodology. Due to the differences in dataset from the one used in Table 4, the raw returns and CAPM alphas for the single sorted portfolios do not compare to the ones in Section 5.1.4. For example, the alpha for the short leg of RSI is slightly more negative at -0.86% compared to -0.78%.

announcements, excluding neutral announcements, indicating that much of the trading profit arises from these more informative disclosures. The next-month alpha on the short leg of RSI is –4.07*** following months with negative earnings announcements and –4.83*** following months with positive earnings announcements. This suggests that short sellers anticipate that the negative market reaction to bad news will be priced in over time, expecting the market to continue reacting negatively. On the other hand, after positive earnings announcements, short sellers might anticipate a reversal of the positive returns, possibly believing that the market overreacted to the good news, leading to a subsequent decline in stock prices. For the long-short hedge portfolios, the alpha is 5.24*** for negative EAs and 4.27** for positive EAs. The results suggest that this difference stems from the asymmetry in return distribution across the long and short legs portfolios following negative EAs compared to positive EAs. Namely, the long leg of negative EAs shows a positive (though statistically insignificant) alpha of 1.18, while the long leg of positive EAs shows a slightly negative (also statistically insignificant) alpha of -0.56. This explains the higher hedge portfolio alpha for negative EAs compared to positive EAs, and could also explain why only the interaction term between RSI and negative earnings announcements was negative and significant in the regressions in Table 11.

Overall, these results support our third hypothesis (see Section 2.4), showing that short sellers generate abnormal returns by efficiently responding to earnings announcement news, and do, by finding that the hedge portfolio alphas remain positive and significant when using residual RSI (controlling for anomaly signals), provide an explanation for the negative RSI-return relationship that extends beyond the use of public anomalies. In addition to this, the analysis provides interesting insights about short sellers' effective reactions to news events by contrasting the returns generated after negative news events to those generated after positive ones.

6 Conclusion

This paper explores the informational role of short sellers by investigating the mechanisms behind the well-established negative relationship between short interest and subsequent stock returns. Using a rich dataset covering Nordic equity markets from 2020 to 2025, we test three interrelated hypotheses: (1) whether short sellers systematically target stocks with well-known pricing anomalies, (2) whether they anticipate future earnings surprises beyond what anomaly signals explain, and (3) whether they respond more efficiently to public information releases, particularly earnings announcements.

Our empirical results support all three hypotheses. First, we find that a substantial part of short sellers' abnormal returns can be attributed to their exploitation of established anomaly signals. Second, short interest is a strong predictor of future negative earnings surprises, even after controlling for anomaly exposures, suggesting that short sellers possess forecasting ability regarding firm fundamentals. Third, we show that the predictive power of short interest intensifies during earnings announcement months. The negative relationship between short interest and subsequent returns becomes significantly stronger around these events, indicating that short sellers not only anticipate bad news but also react to public information more effectively than other market participants. Finally, we conduct all tests related to our second and third hypotheses on both raw RSI and the residual RSI from a regression of RSI on anomaly signals. This extension allows us to conclude that earnings surprise anticipation and superior reactions to earnings announcements are complementary to anomaly exploitation in explaining the abnormal returns generated by short sellers. Taken together, these findings highlight that short sellers are sophisticated traders who derive a significant portion of their edge from superior processing of public information and reactions to news events. Furthermore, this finding also aligns with a branch of related literature indicating that informed short sellers enhance market efficiency by correcting mispricing.

This study, however, is subject to several limitations. First, our use of monthly data limits our ability to capture intra-month shorting flows, especially around earnings events where market reactions unfold over shorter time frames. Second, our analysis is restricted to Nordic equity markets, which, while offering transparent short interest data, may not reflect conditions in larger or more fragmented markets. Third, our analysis focuses on established pricing anomalies and does not incorporate other potentially informative signals, such as investor sentiment, analyst forecast revisions, or insider trading activity. Finally, the proxies used for short sale constraints - firm size and illiquidity - are indirect and may not capture the full extent of short sale constraints.

Future research could investigate how short sellers influence price discovery, quantifying the extent to which they, through informed trading, contribute to market efficiency. It would also be valuable to examine which types of short sellers, such as institutional investors, hedge funds, or retail traders, hold the greatest informational advantage, as this would clarify how information enters markets and reveal which participants play the most critical role in enhancing efficiency. Finally, expanding the analysis to a pan-European context could test the generalizability of our findings across different markets.

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A Appendix

A.1 Raw Returns and CAPM alphas individual anomaly quintile portfolios

Table 13: Raw Returns and CAPM Alphas for anomaly variables (see Section 4.2.1 for methodology)

Panel A: Raw Returns			
	Long	**Short**	**Long-Short**
BM	0.59***	0.19	0.40*
MOM	1.09***	-0.25**	1.34***
O-Score	1.61***	-0.57	2.18
NSI	1.49***	-1.09	2.58***
CEI	1.68***	-0.77	2.45***
TACC	0.82	0.75	0.08
NOA	-0.08	1.05***	-1.14**
GPP	1.56***	-1.34	2.91
AG	-1.09	-0.15	-0.94
ROA	1.56***	-1.95	3.51
ITA	0.14***	0.30***	-0.16*
Panel B: CAPM Alphas			
	Long	**Short**	**Long-Short**
BM	-0.74**	-0.88***	0.14
MOM	-0.03	-1.77***	1.74***
O-Score	0.44*	-1.79***	2.23***
NSI	0.52***	-2.34***	2.87***
CEI	0.50***	-1.96***	2.46***
TACC	-0.35	-0.59*	0.23
NOA	-1.25***	-0.15	-1.10**
GPP	0.43	-2.63***	3.06***
AG	-2.25***	-1.44***	-0.81
ROA	0.36*	-3.25***	3.61***
ITA	-0.96**	-0.98**	0.02

Note: This table presents next-month raw returns (Panel A) and CAPM alphas (Panel B) for portfolios sorts based on the values of the 11 anomaly variables. The short (long) legs are the quintile portfolios predicted by literature to yield the lowest (highest) subsequent return (see Section 3.4). T-statistics are adjusted for heteroskedasticity and autocorrelation in line with Newey and West (1987). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

A.2 Returns and alphas for 5x5 portfolios double-sorted on RSI and PERC

Table 14: Returns and alphas on portfolios formed by 5 x 5 independent double sorted (see Section 4.2.4) for methodology

Panel A: Raw Returns

Anomaly Quintiles	High RSI (Short)	2	3	4	Low RSI (Long)	Low-High (Long-Short)
PERC						
Short Leg (S)	-0.45	-2.78***	-1.23	-0.62	-0.16	0.28
2	0.15	-1.30*	-0.51	-1.01	0.18	0.02
3	0.69	1.30***	0.85	0.44	2.16**	1.48
4	1.20***	1.91***	1.09**	0.30	1.92**	0.73
Long Leg (L)	0.98**	0.91**	1.68***	1.96***	1.38***	0.40
L-S	1.43	3.69***	2.91**	2.58**	1.54	-0.11

Panel B: CAPM alpha

Anomaly Quintiles	High RSI (Short)	2	3	4	Low RSI (Long)	Low-High (Long-Short)
PERC						
Short Leg (S)	-2.03*	-4.47***	-2.78***	-1.77**	-1.80**	0.23
2	-1.44**	-2.82***	-1.66*	-2.44***	-0.70	0.74
3	-0.50	0.09	-1.05*	-1.26**	0.70	1.20
4	-0.08	0.94**	-0.06	-0.45	0.79	0.87
Long Leg (L)	-0.28	0.17	0.97*	0.83	0.30	0.58
L-S	1.74	4.64***	3.75***	2.60**	2.09**	0.35

Note: This table reports raw returns and CAPM alphas for double-sorted portfolios sorted by the quintiles of RSI and *PERC*. Raw returns and CAPM alphas are presented for each of the 5 x 5 intersections and hedge portfolios. T-statistics are adjusted for heteroskedasticity and autocorrelation in line with Newey and West (1987). *, **, and *** indicate statistical significance at the 0.10, 0.05, and 0.01 level, respectively.

A.3 Summary statistics for more narrow dataset with non-missing earnings announcement dates

Table 15: Summary statistics of RSI and market capitalization for dataset used for earnings announcements

	Mean	**Median**	**Std. Dev.**
RSI	2.03	1.12	2.52
MCAP	4321	1653	6699
No. of unique ISIN	166		

Note: This table reports the time series averages for the mean, median, standard deviation RSI and market capitalization variables for the smaller dataset used in earnings announcements tests. The sample period is from 2020 - 2025. The regressions in Table 11 and the portfolios sorting in Table 12 are conducted on this dataset filtered on a threshold for the amount of non-missing earnings announcement dates, see Section 4.3.2 for methodology

AI Disclosure

This thesis has incorporated the use of AI tools, including Chat GPT and GitHub CoPilot, in two main ways. First, it was used to help identify and resolve issues within the coding, as well as to offer suggestions for improving the layout and clarity of graphical outputs. Second, it provided support in refining the written content by enhancing clarity, fluency, and grammatical accuracy.

We recognize that the use of AI tools such as Chat GPT comes with certain risks. These include the risk of generating incorrect or suboptimal code. Additionally, the textual suggestions produced by AI tools occasionally lack depth or cohesion, necessitating careful oversight. To manage these risks, we have taken a cautious approach. All AI-generated code and text has been independently verified and revised to ensure accuracy and reliability.