Norges Handelshøyskole

FIN11 Trading and Market Microstructure

FIN11 Term paper

Predefined Information

Start date:	04-11-2025 09:00 CET
End date:	08-12-2025 12:15 CET
Examination type:	Term paper (70%)
Term:	2025 12
Grading scale:	Norwegian 6-point scale (A-F)
Flow code:	191 FIN11 1 O3 2025 12
External assessor:	External assessor 1
Internal assessor:	Internal assessor 1

Participant

Candidate No.:	1026

Information from participant

Can the submission be used anonymously for educational purposes?:
Yes

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Group name:	(Anonymised)
Group number:	8
Other members:	1052, 1061, 1072

In which language did you write your answer paper? *

English



*Word count: 6573**
**Excluding graphs, equations etc.*

Abstract

From 2013 to 2021, Sindre Finnes, husband of former Norwegian prime minister Erna Solberg, executed several thousand trades on Oslo Børs. The disclosure of his trading sparked speculation that he must have outperformed the market, especially given the potential for an informational advantage. This paper examines whether his realised returns support that claim and what his case reveals about retail trading behaviour. Using his published transaction record combined with Norwegian equity and factor data, we reconstruct an approximate portfolio path, compute risk-adjusted returns and analyse trading intensity, costs and performance around each trade. The Carhart four-factor regression shows a negative, statistically insignificant alpha and a beta well above one, indicating that Finnes bears more market risk without earning excess returns. His portfolio index fails to keep up with a simple OSEBX benchmark once conservative transaction costs are included. Turnover is extremely high, and post-trade cumulative abnormal returns are unfavourable, consistent with behavioural patterns such as overtrading, “buying the dip” and the disposition effect. Overall, the case illustrates how intensive, leveraged retail trading can produce modest or weak outcomes even without dramatic blow-ups. It reinforces the view that low-cost diversified investing is hard to beat in a largely efficient market.

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1. Introduction

"Perhaps the biggest political scandal in Norwegian history"- Kim Arne Hammerstad

(Finansavisen, 2023)

In autumn 2023, revelations about Sindre Finnes' stock trading prompted a nationwide debate about trust, rules and markets. From October 2013 to October 2021, Finnes' wife, Erna Solberg, served as Norway's prime minister, while Finnes was actively trading in companies influenced by Solberg's policies.

Following these revelations, Økokrim, the specialized unit investigating economic crimes in Norway, reviewed Sindre Finnes' trading activity. Økokrim concluded that there was no basis to open an investigation into insider trading or violations of the Securities Trading Act. Økokrim's director, Pål. K. Lønseth stated the following:

> *"There is nothing special about Finnes' (trading), on the contrary he could have done better… Finnes has not hit remarkably well, which in isolation could have been an indication of insider trading." - Pål K. Lønseth*

(Diaz et al., 2023)

Consequently, this paper sets aside legal and ethical questions concerning the case and instead evaluates Finnes' performance during Solberg's period as the prime minister of Norway. We address the following research question:

How does Sindre Finnes' trading performance compare to the market, and what insights does it provide about retail trading behavior?

The paper begins by presenting the background of our case to provide the reader with essential context, followed by an outline of the theoretical framework. This framework highlights why it is so difficult for a retail investor to beat the market and identifies the aspects of Finnes' performance we examine. Before turning to the data, we describe the assumptions and

delimitations applied. The paper then presents Finnes' descriptive trading statistics, including an evaluation of his performance and use of leverage. Next, we outline the methodology, including the relevant performance measures and financial models, before turning to the paper's central section, the analysis, where we present the key findings. The paper concludes by answering the research question, then reflecting on further research.

2. Background

2.1 Sindre Finnes

Finnes served as a policy director at Norsk Industri, a major industry lobby organization. During Solberg's tenure, he engaged in extensive personal trading in equities listed on Oslo Børs. In the aftermath of the scandal, he made all his trades publicly available. He executed more than 3,290 trades in the period from 2013 to 2021. His trading also involved leveraged positions, which carry significant risk, even for professional full-time traders (Nilsen et al., 2023). Over the period, he bought and sold financial products for a total of NOK 125 million (Bakken et al., 2023). In the end, Finnes had gained roughly NOK 2.2 million and lost NOK 1.9 million, resulting in a net profit of approximately NOK 250,000 over the eight years of active trading (Eberhard-Gran & Røsvik, 2023).

2.2 Interview

While working on this term paper, we contacted Sindre Finnes directly, but despite several attempts, we received no response. We had the opportunity to interview Robert Næss, Investment Director at Nordea, who appeared frequently in Norwegian news outlets following the scandal.

3. Theoretical Framework

3.1 Beating the market

For retail traders, performance is typically measured against a market index such as the OSEBX (the Oslo Børs Benchmark Index). The Efficient Market Hypothesis is a fundamental theory in financial economics, which states that asset prices fully and immediately reflect all available information. It distinguishes between three forms of market efficiency. First, in weak-form, asset prices reflect all past market information. In semi-strong form, prices reflect all publicly available information. Lastly, in strong-form markets prices reflect both public and private information

(Fama, 1970). The empirical evidence suggests that markets are generally semi-strong-form efficient with respect to easily obtained and easily interpreted public information (Harris, 2003, p. 253). Consequently, the market leaves little room for investors to achieve abnormal returns in the long run.

3.2 Overtrading

Overtrading is the tendency to transact far more than warranted by fundamentals, typically driven by overconfidence and a belief in short-term signals. Decades of evidence show that higher turnover is associated with lower net returns after costs (Barber & Odean, 2000; French, 2008; Odean, 1999). This stands in sharp contrast to long-horizon professionals such as Robert Næss, who advocate concentrated ownership, long holding periods, and low portfolio turnover.

> *"Many people think of stocks as something you 'trade' and believe that trading itself creates value. That is wrong. Too much cost when you trade means you are almost guaranteed to do poorly." – Robert Næss*

(Personal communication, November 14, 2025)

Empirical evidence shows that individual investors with very high turnover systematically underperform simple buy-and-hold benchmarks once trading costs are taken into account (Barber & Odean, 2000; Barber & Odean, 2001). This high-frequency, short-horizon style stands in sharp contrast to the low-turnover, fundamentals-driven discipline typically emphasized for professional, career investors (Frazzini et al., 2018).

3.3 Transaction costs

Transaction costs are the expenses associated with buying or selling financial assets. Traders monitor these costs because they make the implementation of trading strategies expensive. Speculative strategies often fail simply because transaction costs outweigh any gross trading profit (Harris, 2003). This is relevant to our paper, as transaction costs can be decisive for high-volume traders such as Finnes.

3.4 Behavioral Finance

Behavioral finance is an important perspective for understanding trader behavior and explaining common patterns in their decision-making.

The disposition effect, first formulated by Shefrin and Statman (1985), refers to traders' tendency to sell stocks that have risen in value (winning stocks) too early and hold on to stocks that have fallen in value (losing stocks) for too long. Several factors, such as prospect theory, regret aversion and self-control issues, can explain the disposition effect. The disposition effect gives a clear picture of real-world deviations from rational behavior (Shefrin & Statman, 1985).

Familiarity bias refers to investors' tendency to allocate disproportionate amounts of their investments to assets that feel "close" to them. This typically means investing in their home market, local firms, their own employer, or industries they work in. Instead of diversifying broadly, individual investors tend to narrow their opportunity to what they recognize and feel comfortable with.

Empirical research shows that investors with strong home and local biases do not earn superior returns (Barber & Odean, 2011). Their underdiversified portfolios tend to have a lower risk-adjusted performance than simple, broadly diversified benchmarks. Døskeland and Hvide (2011) find a similar pattern for Norwegian investors. Those who overweight professionally close stocks or companies operating in the same industry as the investor's employer do not achieve positive alpha (Døskeland & Hvide, 2011). The behavior is therefore best understood as overconfidence in perceived knowledge, rather than as rational use of an informational advantage.

"Buy-the-dip" is a common heuristic in which traders purchase a stock after a sharp decline in value. A heuristic is a mental shortcut that enables quick decisions with minimal cognitive effort. A strategy based on buying the dip requires precise timing, and despite its intuitive appeal there is no strong empirical evidence that it generates abnormal returns (Bonini, S., Shohfi, T., & Simaan, M., 2024).

Taken together, these concepts highlight systematic deviations from fully rational behavior that can materially affect trading decisions and long-run performance.

4. Data, assumptions and delimitations

This section presents the data assumptions underlying our analysis. Our aim is not to reconstruct Sindre Finnes' exact wealth, but to use a transparent trading record and standard market data to evaluate whether his realized returns are consistent with the Efficient Market Hypothesis (EMH) for a high-turnover retail investor, and to characterize the extent of overtrading in his portfolio.

Our analysis uses three main inputs: Finnes' official transaction list, mid-price data for all relevant securities and the benchmark index, and Norwegian factor returns and the risk-free rate for the Carhart four-factor model.

4.1 Data sources

4.1.1 Trading list

We obtained Finnes' transaction list from a public source (Nilsen et al., 2023). For analysis, we created two versions of the file, one sorted by time and one grouped by ticker. The original file contains the trade date, security name, side, quantity, trade price, and platform. The transaction list contains 3,289 observations spanning from 29/09/2013 to 13/10/2021, the period Solberg served as prime minister.

The "security name" field mixes the company name with instrument tags (gearing and bull/bear). To simplify downstream work, we added separate variables for ticker, gearing and bull/bear side, and we normalized side to BUY/SELL. Because some companies changed names during the period, we manually mapped historical names to a consistent ticker key and retained both the original label and the standardized ticker for traceability.

4.1.2 Market data

Using Bloomberg, we retrieved daily mid-price series for every ticker in the trading list and for OSEBX, the main index. We pulled data from October 2012 to October 2022 to provide sufficient pre- and post-trade history. All prices were stored as time series with dates in dd/mm/yyyy format and later converted to daily log returns. To ensure compatibility across files, we standardized date formats and aligned all tickers to the same naming convention used in the trading list.

4.1.3 Carhart factors and risk-free rate

We obtained the factor data from Bernt Arne Ødegaard's Norwegian equity market data library. The dataset provides monthly Norwegian versions of the market, size (SMB), value (HML) and momentum (UMD or PR1YR) factors, as well as the one-month risk-free rate. These series are constructed from OSEBX stocks and are therefore consistent with the market relevant for Finnes' trades and for our OSEBX benchmark (Ødegaard, 2024). Using Ødegaard's factors ensures that our Carhart specification is based on a transparent and widely used source for the Norwegian equity market.

4.2 Missing information

Several media outlets, including Faktisk.no and Dagens Næringsliv, point out that the list contains gaps and irregularities. It is unknown which shares Finnes held before the starting date. For several companies, the reported position becomes negative during the period. Since an investor cannot sell more shares than they own, this implies pre-existing holdings that are not recorded. We therefore only observe changes within the reported interval.

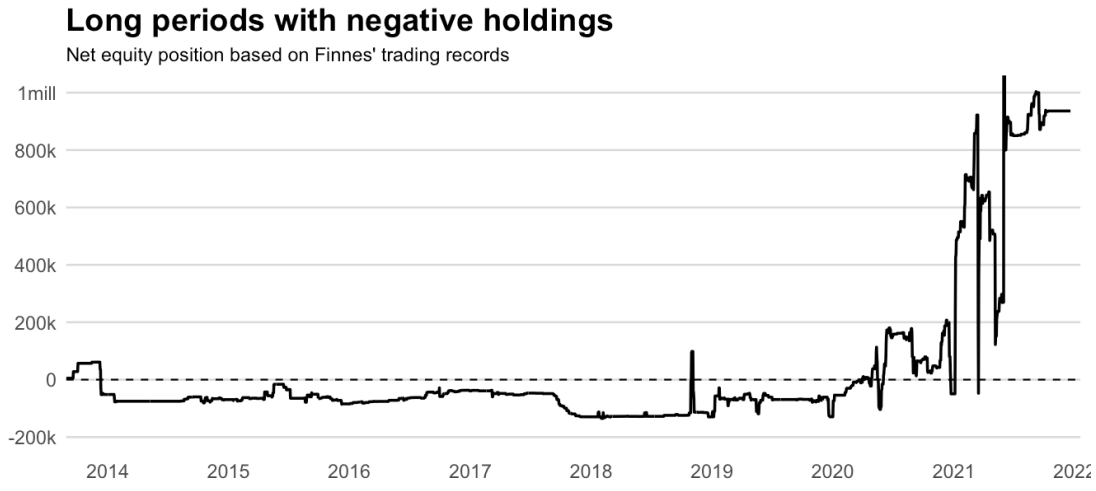


Figure 1: Net equity positions based on Finnes' trading records

Figure 1 illustrates these inconsistencies at portfolio level, with long stretches of negative reported holdings that cannot reflect an actual equity position. We therefore treat the dataset as a record of reported transactions rather than a complete, internally consistent reconstruction of

Finnes' wealth. Where the data allow clear inferences, we comment on timing, direction and concentration of trades, but avoid drawing conclusions that would require precise knowledge of his initial holdings or exact net exposure. Results should be read as patterns in the available trading record, not as a full account of all positions he held.

4.3 Transaction costs

To approximate the commissions Finnes paid, we assume he traded under the VIP customer fee rates at Nordnet and the Premium customer fee rates at DNB. For Nordnet, we apply a fee of 0.035% with a minimum of NOK 39 for trades in the Nordic markets, and 0.08% with a minimum of NOK 79 outside the Nordics. For DNB, we apply 0.04% with a minimum of NOK 49 in the Nordic markets, and 0.09% with a minimum of 9 USD outside the Nordics. The commission rates are based on the fee schedules that were publicly available at the time of our analysis (DNB, 2025; Nordnet, 2025).

4.4 Justification of data and assumptions

The transaction file compiled by Nilsen et al. (2023) is not the only reconstruction of Finnes' trading, but it is one of the most accurate sources available. The dataset has been used as an empirical basis for several major news stories about the case and is therefore a natural foundation for our analysis. Our objective is to use this file to describe his behavior and evaluate whether the realized pattern of returns is consistent with what the literature predicts for a high-turnover retail investor. The dataset offers a structured list of all reported trades with the information we need to address the research question.

For price data, we only observe the transaction date, not the exact execution time. Finnes often trades the same stock multiple times within a day, which makes it inappropriate to assume that all orders were executed at the official closing price. We therefore use daily mid-prices from Bloomberg as a consistent approximation for both trade and valuation prices. This necessarily introduces measurement error at the level of individual trades, but such noise should average out across more than 3,000 transactions. Moreover, our main results are expressed in relative terms, such as factor-adjusted returns and event-window CAR, rather than in exact NOK amounts.

The remaining inputs follow standard practice. Norwegian market, size, value and momentum factors and the one-month risk-free rate are taken from Ødegaard's (2024) equity data library.

This dataset is widely used in empirical work on Oslo Børs and aligns with our OSEBX benchmark. Assumptions about transaction costs are conservative, as we assume Finnes traded at some of the lowest retail commission rates available. We also ignore bid–ask spreads and any financing costs. This biases total cost estimates downward. If we still find weak net performance under these favorable assumptions, assuming higher fees would only strengthen our conclusions.

5. Methodology

In this section we describe how we translate Sindre Finnes' trading record into quantitative performance and behavioral metrics. The goal is not to reconstruct his exact wealth, but to evaluate whether his realized returns are consistent with what the Efficient Market Hypothesis (EMH) would predict for a high-turnover retail investor, and to characterize the extent of overtrading in his portfolio.

5.1 Carhart four-factor model

The Carhart four-factor model is an asset pricing model developed by Mark Carhart in 1997. It is an extension of the Fama-French Three Factor Model, which adds the size and value risk factors to the CAPM. Carhart's model introduces a momentum factor to account for the persistence of over- and underperforming stocks. His research showed that stocks with high returns over the past year tend to continue performing well, while those with low returns continue performing poorly (Carhart, 1997).

Recent Nordic evidence indicates that the Fama-French five-factor model does not reliably price differences in average returns in the Nordic markets and often adds little beyond simpler alternatives (Gardtman & Kåll, 2020; Grimeland, 2018). Model comparison studies find that the four-factor model with momentum delivers tighter alphas and better explanatory power in small, Nordic markets, such as Norway (Lahtinen, 2025; Olsson, 2019).

Momentum is also empirically present on Oslo Børs, with winner-loser strategies earning statistically significant premia over long samples, which supports using a model that includes an explicit momentum factor (Absalonsen & Vas, 2014; Ødegaard, 2021). On this basis, and given our available data, we chose the Carhart four-factor model as the primary benchmark.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1\left(R_{M,t} - R_{f,t}\right) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 PR1YR_t + \varepsilon_{i,t} \quad (5.1)$$

Equation 5.1: Carhart four-factor model

Where:

$R_{i,t} = Total\ return\ on\ stock\ or\ portfolio\ i\ at\ time\ t$

$R_{f,t} = Risk - free\ rate\ at\ time\ t$

$R_{M,t} = Total\ market\ portfolio\ return\ at\ time\ t$

SMB $(Small\ minus\ big)$ is a measure of the difference in returns between small and large stocks

HML $(High\ minus\ low)$ is a measure of the spread of returns between the highest and lowest performing stock in each portfolio.

$PR1YR$ is a measure of the return spread between recent winners and losers, computed From performance over the past 12 months, excluding the most recent month

$\alpha_i = Abnormal\ return\ (intercept)\ for\ i\ after\ controlling\ for\ the\ factors$

The model is estimated by ordinary least squares (OLS) over all months for our dataset. The intercept α measures whether Finnes outperforms a passive, risk-adjusted benchmark. A positive and statistically significant alpha would indicate that he beats the market given his exposure to systematic risk.

5.1.1 Calculating monthly portfolio returns ($R_{P,t}$)

By using his transaction record and daily stock prices, we reconstruct Finnes' portfolio day by day. For each trade, we observe date, ticker, side and size. We first aggregate to net traded volume per ticker and day, treating buys as positive and sells as negative. For each ticker, we then cumulate these net flows over time to obtain a time series of share positions.

As addressed in Section 4.2 (Missing information), the sample starts after Finnes already held stocks, and the cumulative position is therefore negative early in the series. To avoid this, we implemented an implied initial holding for each stock. For each ticker i we calculate the minimum of the cumulative series, and if this minimum is negative, we add its absolute value as a constant to the entire series. This shifts the lowest point to zero, yielding a non-negative position path that is consistent with the observed buys and sells in our dataset.

For each stock i and day t we define the start-of-day position as the previous end-of-day position.

$$Shares_{i,t}^{start} = Shares_{i,t-1}^{end}$$

We then calculate the daily stock returns by:

$$R_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1 \tag{5.2}$$

Equation 5.2: Daily stock returns

Where:

$$P_{i,t} = Price\ of\ stock\ i\ at\ the\ end\ of\ day\ t$$

The start-of-day portfolio value is therefore

$$V_t = \sum_i Shares_{i,t}^{start} * P_{i,t-1} \tag{5.3}$$

Equation 5.3: Value of portfolio, start-of-day

The daily portfolio return is the value-weighted average of the stock returns:

$$R_{P,t} = \frac{\sum_i Shares_{i,t-1}^{start} P_{i,t-1} R_{i,t}}{\sum_i Shares_{i,t-1}^{start} P_{i,t-1}} \tag{5.4}$$

Equation 5.4: Daily portfolio return

This ensures that portfolio returns only reflect price movements on the capital invested at the beginning of the day, while trades on day t affect portfolio weights from day $t + 1$ onwards.

5.2 Cumulative abnormal returns (CAR)

We measure short-horizon performance using cumulative abnormal returns (CAR) around each trade. Abnormal returns are defined relative to the OSEBX. Trading day is set to $t = 0$. For each trade in stock i, we first compute daily abnormal returns as

$$AR_{i,t} = R_{i,t} - R_{M,t} \tag{5.5}$$

Equation 5.5: Measuring abnormal returns

Where:

$$R_{i,t} = Return\ of\ stock, i, on\ day\ t$$

$R_{M,t} = Return\ of\ market\ (in\ our\ case\ the\ OSEBX), m, on\ day\ t$

To avoid intraday effects and the fact that we do not observe the exact time of the transaction, we exclude the event day itself and define post-trade cumulative abnormal returns over two time periods:

$$CAR_i\ (0,5) = \sum_{t=1}^{5} AR_{i,t} \quad \& \quad CAR_i\ (0,20) = \sum_{t=1}^{20} AR_{i,t} \tag{5.6}$$

Equation 5.6: Measuring cumulative abnormal returns, 5- and 20-days post-trade.

To evaluate whether trades are typically in the right direction, we condition on the trade side. For buy trades, a positive post-trade CAR is desirable, while for sell trades, a negative post-trade CAR is desirable. We therefore multiply CAR by -1 for sell trades so the value is positive when the realized price development supports the trading decision, and negative when it does not. As a robust check, we also calculated a CAR in a pre-trade window, -20 to -1 relative to the trade date. This measure captures whether the trader tends to react to past relative price movements, by examining cumulative abnormal returns before the transaction.

To formally test whether Finnes' trades generate systematically positive or negative abnormal returns, we apply the Wilcoxon signed-rank test to the cross-section of CAR. For each event window, we take the sample of CAR values across all trades and test the null hypothesis that the median CAR equals zero. The Wilcoxon test ranks the CAR values and computes a test statistic based on the sum of the ranks, providing a p-value without assuming normality. A small p-value indicates that the CAR distribution is significantly shifted away from zero, suggesting that trades, on average lead to non-zero abnormal performance rather than random noise.

5.3 Measuring overtrading

Section 3.2 described overtrading as a behavioral pattern where investors rotate their portfolios far more than fundamentals justify, typically resulting in worse net performance once costs are considered. To connect this idea to Sindre Finnes' trading record, we summarize overtrading along two simple, observable dimensions.

First, we use an annual turnover ratio that relates traded volume to the size of the portfolio:

$$Turnover_y = \frac{\sum_{t \in y} \sum_i |\Delta\, Q_{i,t}| * P_{i,t}}{\frac{1}{2}(V_{y,start} + V_{y,end})} \tag{5.7}$$

Equation 5.7: Measuring turnover ratio

Where:

$Turnover_y$ = turnover ratio in calendar year y,

$t \in y$ = all the trading days that belong to year y,

i = indexes individual instruments in the portfolio,

$\Delta Q_{i,t}$ = the change in the number of units of instrument i between $t-1$ and day t; the absolute value $|\Delta Q_{i,t}|$ ensures that both buys and sells count as positive traded volume,

$P_{i,t}$ = price per unit of instrument i on day t,

$V_{y,start}$ = the total market value of the portfolio at the start of year y (first trading day),

$V_{y,end}$ = the total market value of the portfolio at the end of year y (last trading day).

The denominator $\frac{1}{2}(V_{y,start} + V_{y,end})$ is the average portfolio value over the year, so $Turnover_y$ measures how many times the portfolio is effectively "rotated" during year y.

Second, we track trading frequency as the share of trading days with at least one transaction:

$$Trading\ frequency = \frac{Number\ of\ days\ with\ at\ least\ one\ trade}{Total\ number\ of\ trading\ days} \quad (5.8)$$

Equation 5.8: Trading frequency.

This captures how continuously the investor is active in the market.

5.4 Transaction costs

To estimate Finnes' total transaction costs, we combine the complete trade-by-trade dataset with the assumed commission fees for Nordnet and DNB, as clarified above. For each recorded trade, we use the trade value and classify the transaction by broker and market (Nordic or non-Nordic). We then apply the relevant commission rate to the trade value and set the fee for each trade equal to either the percentage rate or the minimum fee, whichever is larger. Since costs apply to both purchases and sales, this calculation is performed for each buy and sell order in the dataset. Finally, we sum the resulting fees across all trades to estimate Finnes' total explicit brokerage costs over the period.

6. Descriptive statistics

This section summarizes key features of Finnes' trading on the OSEBX between 2013 and 2021. He traded in 81 different securities, often using leveraged products.

6.1 Finnes' trading characteristics

Finnes' trading intensity increased steadily throughout the period, peaking in 2020 when he averaged 4.36 trades per day. From 2019 onwards his average trade size roughly doubled compared to earlier years and remained at this higher level for the rest of Solberg's period as prime minister.

Year	Total trades:	Trades per trading day:	Average trade size:	Total volume:
2013	62	0.25	NOK 23 558.00	NOK 989 448.00
2014	83	0.33	NOK 24 712.00	NOK 2 075 870.00
2015	196	0.78	NOK 16 840.00	NOK 3 283 553.00
2016	234	0.93	NOK 13 589.00	NOK 3 179 990.00
2017	300	1.19	NOK 36 152.00	NOK 10 845 666.00
2018	315	1.25	NOK 25 225.00	NOK 7 945 847.00
2019	443	1.76	NOK 51 240.00	NOK 22 697 372.00
2020	1099	4.36	NOK 40 381.00	NOK 44 387 896.00
2021	558	2.21	NOK 53 871.00	NOK 30 060 145.00
In total	3289	1.45	NOK 31 729.00	NOK 125 456 787.00

Table 1: Overview of Finnes' yearly trading activity

Overall, Finnes' behavior can be described as an extreme case of high-turnover retail trading. As portfolio manager Robert Næss summarized in our interview, *"for a private individual who has no information advantage but just trades based on what they think is knowledge, it is basically the case that the more you trade, the worse it gets"* (Personal communication, November 14, 2025).

6.2 Evolution of portfolio

Furthermore, we examine the portfolio outcomes implied by this activity, using the transaction records in VG's dataset (Nilsen et al., 2023) to reconstruct his portfolio value over time.

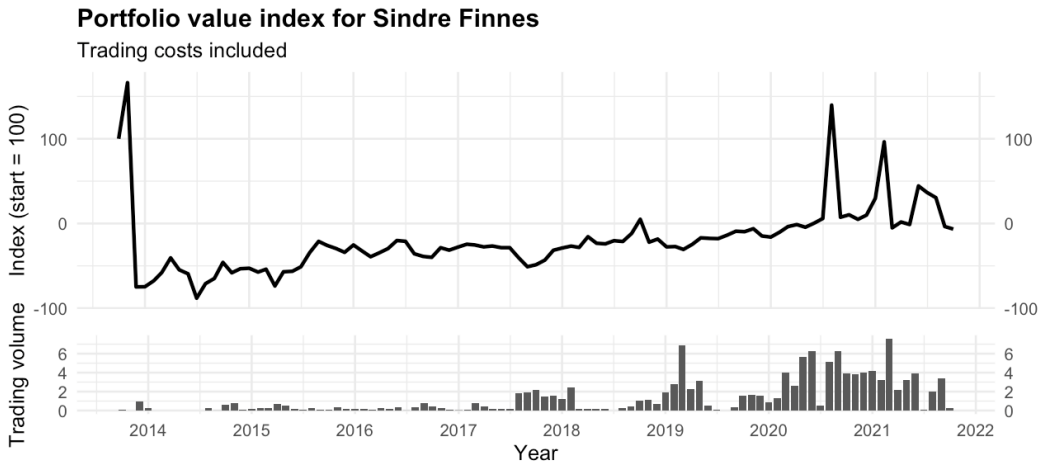


Figure 2: Portfolio value index for Sindre Finnes.

Figure 2 shows a portfolio index normalised to 100 in October 2013, with transaction costs included. The index falls sharply during the first year and never displays a sustained compounding pattern. Instead, it fluctuates around a relatively low level compared with the starting point, with occasional spikes followed by drawdowns. This pattern is consistent with overtrading, as Finnes increasingly rotates large positions while costs and drawdowns absorb temporary gains. Given the data limitations discussed in Section 4.2, the absolute level of the index should be interpreted cautiously.

To illustrate the two spikes in Figure 2, Table 2 summarizes realized gains and losses around each episode.

Dates / episode:	Amount (realised result):	Securities (main posistions):	Leverage type:	Drivers:
2020: Upwards trend before spike one:	NOK 2 240 260.00	ABL, WAWI, MGN, NEL, KAHOT, NHY, NEL BEAR X5, DAX BULL (X15, X5)	Mainly single equities, and leveraged OBX/DAX products (bull/bear X10, X3)	Covid-related re-pricing and green/tech wave
2020: Lose after the spike:	-NOK 2 378 541.00	HEX, ARR, OSEBX BULL X5/X10, NEL BULL X3, SAGA	Highly leveraged OBX/DAX bull and bear sertificates + individual stock with high risk	Trying to "trade" the top with leverage
P&L from the period:	-NOK 138 281.00			
2021: Upwards trend before spike two:	NOK 2 035 838.00	NKR, WAWI, NEL, NHY, ELK, OSEBX BULL X10, S&P 500 X10, DAX BULL X10	Combination of individual stocks and levarged indexes (OBX/DAX/S&P)	Momentum and event driven trades in stocks and leveraged bull products
2021: Loss after the spike	-NOK 2 225 779.00	IDEX, KAHOT, ARR, ABG, SEA1, OSEBX BEAR X5, DAX BEAR X5, XACT OBX Bear ETF, S&P 500 BEAR X5	High risk stocks + leveraged bear-products (OBX/DAX/S&P)	Focusing on speculative small cap companies and leveraged bear products
P&L from the period:	-NOK 189 941.00			

Table 2: Realized trading gains and losses before and after the 2020 and 2021 spikes.

Table 2 summarizes the two striking spikes in 2020 - 2021. In both years, Finnes builds up large, realized gains immediately before the peak and then suffers almost equally significant losses afterwards, so that net P&L over each episode is slightly negative. The spikes therefore reflect round-trip, leveraged trading rather than sustained wealth creation: he can generate sizable profits in the short run, but systematically gives them back in subsequent trades.

To benchmark these outcomes, we compare three alternatives for NOK 100 invested in October 2013, following Finnes' actual trading, placing the money in Robert Næss' actively managed Norwegian equity fund "Norge Verdi", or simply buying the OSEBX index. In our interview, Næss described Norge Verdi as a rare case of long-run active management that has clearly outperformed its benchmark, with roughly 600% cumulative return to clients after fees over the past two decades. Our comparison is approximate, as Finnes' path is reconstructed from trades and estimated costs, while the fund and index series rely on reported net asset values and prices. We work at a monthly frequency and abstract from taxes.

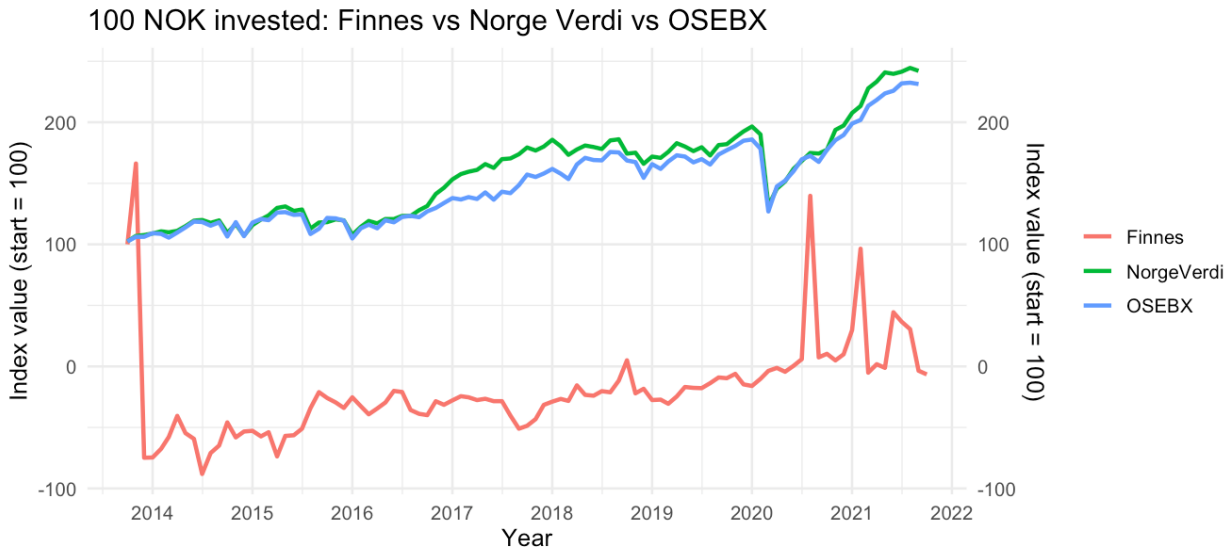


Figure 3: Portfolio evolution for Finnes, Norge Verdi and OSEBX.

Over the sample period, both Norge Verdi and the index show a smooth, compounding increase in value. On the other hand, Finnes' portfolio index remains below its starting level and ends with a loss. Even under these conditions, his high frequency, leveraged trading fails to keep up with either benchmark and, in economic terms, destroys capital over the period.

6.3 Leverage-based trading

Finnes did not limit himself to ordinary share trading. In addition to his cash equity positions, VG's transaction overview and subsequent media coverage show frequent use of derivatives and leveraged products, including instruments explicitly marketed as "bets on a decline" (Nilsen et al., 2023). Dagbladet Børsen further reports that in 2021 he drew on a share-credit facility of approximately NOK 1.1 million, secured against his existing holdings, to buy more stocks on margin (Suvatne, 2023). Taken together, this points to a trading style that relies heavily on borrowed money and geared products.

In our interview, Næss emphasized how costly this approach is for a private investor. As he put it, *"He had a lot of derivatives, and derivatives are the most expensive instruments you can buy. Leveraged products like OBX X4 and X5 pay a lot to the broker house"*. From a professional perspective, repeatedly paying these product and financing costs raises the hurdle dramatically, because before any excess return can appear, fees and interest must first be earned back. Næss also linked the extensive stock-credit line to attitude rather than edge, remarking that *"the fact that he took out a share loan of 1.1 million kroner tells me this is an investor who thinks trading is fun and enjoys the excitement around it"* (Personal communication, November 14, 2025). In other words, leverage here seems more closely tied to thrill-seeking and short-term conviction than to disciplined portfolio construction.

6.4 Stocks and sectors

We finally examine which parts of the market Finnes focused on and how these positions performed. Figure 4 shows the distribution of his trades across GICS sectors.

Industrials and communication services are his two largest exposures, each accounting for close to 30% of all transactions. Energy and information technology together make up roughly another third of his trading, while shipping and sector index products also represent substantial shares. By contrast, financials, consumer staples, materials, and real estate appear only sporadically in the data.

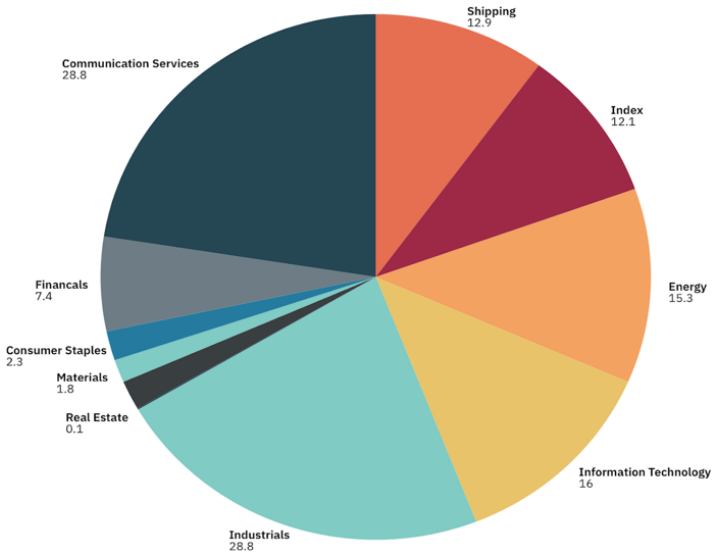


Figure 4: Sector distribution of stocks Finnes traded

Overall, his portfolio is tilted towards industrial and energy-related companies, with relatively limited positions in more traditionally defensive sectors. This pattern is partly consistent with the composition of Oslo Børs, where industrial and energy firms are also strongly represented. Still, it also reflects the sector concentration and lack of broad diversification often documented in the literature on individual investors.

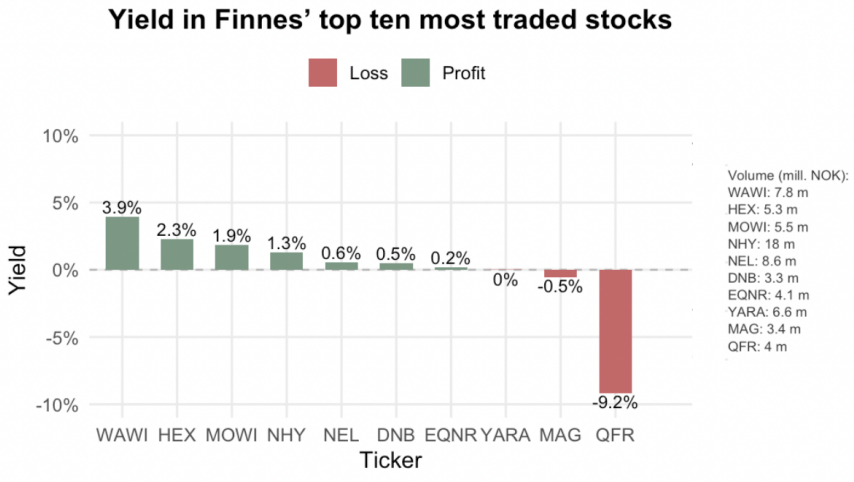


Figure 5: Yield in Finnes' ten most traded stocks.

Figure 5 focuses on Finnes' ten most traded stocks and compares their percentage yields with traded volumes. Turnover is particularly high in Norsk Hydro (NHY), Wallenius Wilhelmsen (WAWI) and Mowi (MOWI), yet realized returns are modest, clustered between 0 and 4%. There is one pronounced outlier, a loss of about 9% in Q-Free (QFR). The combination of high trading intensity and low net yield underlines how little reward he obtained for the risk and effort involved.

7. Analysis

To further examine the research question, the analysis will present results and key findings from our data.

7.1 Key findings

7.1.1 Risk-adjusted performance: Carhart four-factor model

To measure whether Finnes beats the market after adjusting for risk, we estimate a Carhart four-factor regression on Finnes' monthly portfolio excess returns. Table 3 reports the summary output when $R_{P,t} - R_{f,t}$ is regressed on the Norwegian market excess return and the SMB, HML and momentum factors from Ødegaard's dataset. As outlined in the methodology, the intercept α measures abnormal performance after controlling for systematic risk.

Variable	Estimate	Standard error	P-value	R^2	Adjusted R^2
Alpha	-0.00367	0.0128	0.776	0.22	0.19
Market beta	1.38	0.304	0.000016	0.22	0.19
SMB	0.343	0.308	0.268	0.22	0.19
HML	-0.187	0.204	0.363	0.22	0.19
Momentum	-0.0419	0.198	0.833	0.22	0.19

Table 3: Carhart four-factor regression of monthly portfolio excess returns, 2013-2021

The estimated monthly alpha is approximately -0.37, which corresponds to about -4.3% on an annualized basis. This estimate is slightly negative, but the p-value is large, and the 95% confidence interval easily includes zero. In other words, once we adjust for standard risk factors, we cannot reject the hypothesis that Finnes' portfolio earned the same return as a passive benchmark with similar risk. However, there is no statistical evidence of positive risk-adjusted outperformance, and if anything, the point estimate suggests mild underperformance.

By contrast, the loading on the market factor is both economically and statistically significant. The estimated market beta is around 1.4, indicating that Finnes consistently takes more systematic equity risk than the broad Norwegian market. The remaning coefficients are small and statistically insignificant. This suggests that his style is not well captured by a persistent tilt towards small, value or momentum stocks, but rather by undiversified positions in a changing set of stocks. The regression R-squared is 0.22, meaning that roughly one-fifth of the variation in monthly returns is explained by the model while the remainder is distinctive noise, typical for an undiversified, heavily traded portfolio (Ang et al., 2020).

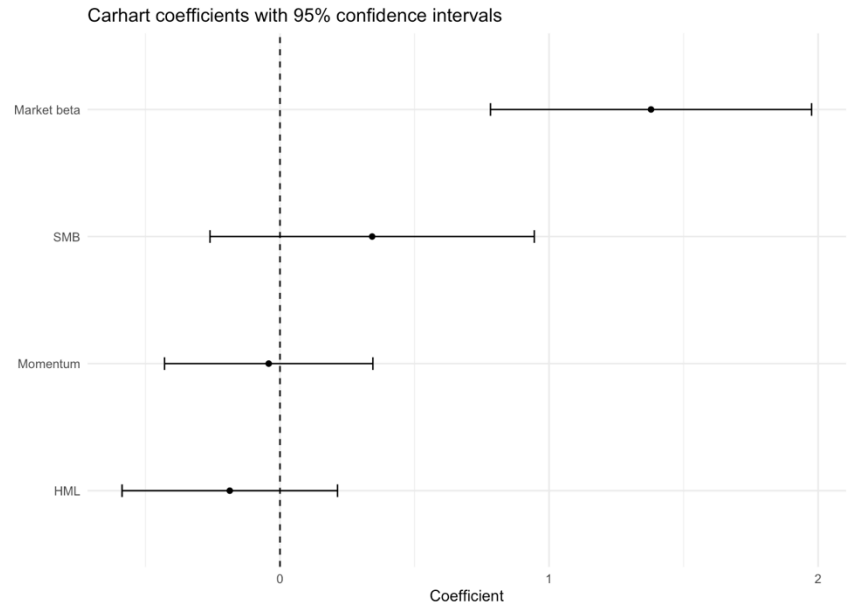


Figure 6: 95% confidence intervals for coefficients from Carhart regression.

Taken together, the Carhart results are consistent with the empirical evidence presented earlier in our theoretical framework. Finnes takes on high market risk and rotates his holdings extremely frequently. The factor-adjusted alpha is indistinguishable from zero and slightly negative in point terms. In that sense his performance resembles the pattern documented for many overtrading retail investors, which is considerable effort and substantial risk-taking, with no robust evidence of skill relative to a simple, low-cost benchmark.

7.1.2 Overtrading

To quantify the extent of Sindre Finnes' overtrading, we first examine his annual portfolio turnover. Using equation 5.7, where turnover in year y is defined as total traded volume divided by the average portfolio value over that year, we calculate turnover for each calendar year from 2013 to 2021. The results are striking: Finnes' annual turnover ranges from 2,485% in 2013 to almost 49,586% in 2020. In more intuitive terms, this means that he effectively "rotates" his portfolio between about 25 and nearly 500 times in a single year. Over the full sample, the average annual turnover is roughly 11,959%, corresponding to trading the portfolio's value around 120 times per year.

These raw numbers already suggest behavior that is far outside what one would typically associate with an individual investor or even an active fund manager. From a purely mechanical standpoint, such activity generates substantial transaction costs. It creates room for poor timing, even before considering whether the trades are based on any genuine informational advantage.

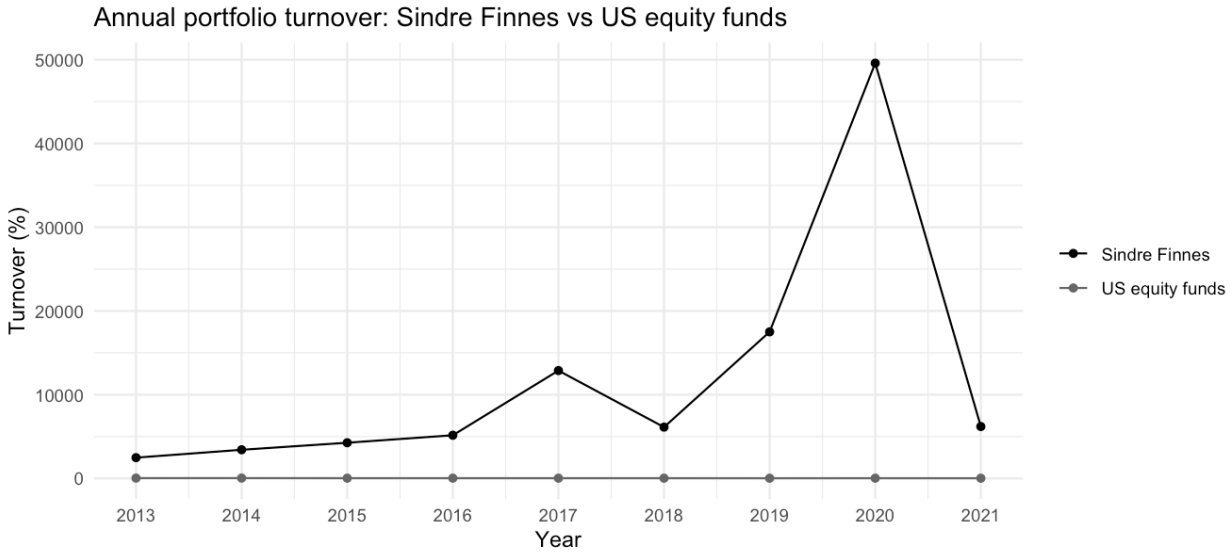


Figure 7: Annual portfolio turnover compared to US equity funds.

To put this into perspective, Figure 7 plots Finnes' annual turnover in the top graph and, in the bottom graph, the asset-weighted turnover of US equity mutual funds based on Investment Company Institute data (Collins et al., 2015). While Finnes' turnover fluctuates between roughly 2,500 and 50,000%, the mutual-fund benchmark stays in a narrow band around 30–45% per year. In other words, a representative actively managed equity fund buys or sells securities

corresponding to about one-third of its portfolio value annually. In contrast, Finnes repeatedly trades several dozen to several hundred times his portfolio value.

Figure 7 makes this gap immediately clear. In every year of the sample, Finnes' turnover is one to two orders of magnitude above the mutual-fund benchmark: in the early years he trades roughly 50–100 times more intensively than a typical equity fund, and by 2018–2020 this multiple increases dramatically. Given the overtrading literature, where high turnover is strongly associated with underperformance after costs, Finnes' behavior places him in the extreme tail of trading intensity. It provides a strong indication that overtrading is likely to have undermined his net returns.

A second dimension of Finnes' behavior is trading frequency, how often he is in the market at all. Measured as the share of Oslo Stock Exchange trading days with at least one trade, his activity rose from about 13% of trading days in 2013 to around 31–41% in 2015–2019. From 2016 onwards, he has been active on roughly every second or third trading day. In 2020 and 2021, this increases to about 70% and 62% respectively, as shown in table 1. The number of trades per day also rise from 0.25 in 2013 to 1.76 in 2019 and to more than 4 trades per day in 2020. This suggests that Finnes is not an occasional market participant, but a consistently active trader. In combination with the extreme turnover documented above, this high trading frequency fits well with Robert Næss' description of Finnes as a high-frequency retail trading where, for an investor without an informational edge, "the more you trade, the worse it gets" (Personal communication, November 14, 2025).

7.1.3 Transaction costs

Based on our assumptions, applying the fee rates trade-by-trade implies that Finnes paid NOK 155,176 in brokerage fees over the period. This high total arises because the fee structure is disadvantageous for his trading style, as percentage rates apply only above trade sizes of roughly NOK 110,000-125,000 in Nordic markets. Most of his trades fall well below these thresholds, leading the minimum commission to bind frequently. His frequent trades in small clips therefore maximize the number of minimum charges. Over thousands of trades this accumulates into a six-figure cost that must be earned before any net outperformance versus OSEBX is possible. Set against his relatively modest net profit, these cost estimates indicate that much of his gross trading gains went to brokers rather than remaining in his portfolio.

It is also important to note that NOK 155,176 should be considered a conservative estimate of total trading costs. It captures only explicit brokerage fees and ignores costs such as bid-ask spreads and market impact from aggressive orders. For a trader who frequently enters and exits positions, these implicit costs are likely to affect net performance negatively. Overall, even if Finnes' stock selection had been slightly profitable before costs, the combination of minimum commissions and high trading frequency made it very difficult for him to "trade his way" to outperformance.

Taken together, the evidence is consistent with the broader microstructure and overtrading literature. It suggests that, without a clear informational edge, high activity combined with binding minimum commissions and other frictions makes it hard for a retail investor to outperform through active trading.

7.1.4 Behavioral patterns in CAR

Our data analysis has identified several systematic patterns consistent with behavioral biases in trading. Across all trades, both 5- and 20-day cumulative abnormal returns after the trade are on average negative, and hit rates are below 50%. When we condition on trade direction, the pattern becomes even clearer, as purchases are on average followed by negative abnormal returns relative to OSEBX, while sales are followed by positive abnormal returns. The Wilcoxon signed-rank tests reject the hypothesis that median CAR is zero, and binomial tests show that the share of trades with a positive CAR is significantly below half. In other words, Finnes' trades tend to be in the wrong direction, both in terms of average CAR and the fraction of trades that add value relative to the index.

Side	N (5d)	Median CAR 5d	Hit-rate 5d	N (20d)	Median CAR 20d	Hit-rate 20d
Buy	1546	-0.6 %	43.1 %	1546	-1.1 %	45.5 %
Sell	1373	0.5 %	43.8 %	1373	0.6 %	48.0 %

Table 4: Buy/sell CAR for 5- and 20-day intervals.



Figure 8: Average CAR after buy and sell, for 5- and 20-day intervals

This pattern is consistent with a variant of the disposition effect. Our results show that the stocks Finnes sells continue to outperform the market over the following weeks, while stocks he buys tend to underperform on average. Selling positions that afterwards do well is an example of the disposition effect, as he realizes gains in stocks that still have momentum. Although our CAR measures are based on trade dates rather than full holding periods, the combination of positive post-sale CAR and negative post-purchase CAR indicates that he frequently realizes winners prematurely and relocates capital to stocks that do not pay off.

Side	N (pre-trade)	Median pre-trade CAR	Share positive	Wilcoxon p-value
Buy	1380	-1.2 %	44.2 %	0
Sell	1238	-0.9 %	46.3 %	0

Table 5: Buy/sell pre-trade CAR, 20 days prior to trade date.

The pre-trade CAR sheds further light on the decision process. For both buys and sells, we find that CAR over the window -20 to -1 is systematically negative, with medians and means significantly below zero. This suggests that Finnes often initiate trades after a period of relative

weakness. For purchases, this is consistent with a "buy-the-dip" heuristic, as he tends to buy stocks that have already underperformed the market in the weeks leading up to the trade, perhaps in the hope of a reversal. Our post-trade CAR results indicate that such reversals are rarely realized. Instead, the underperformance often persists, in line with the empirical literature, which finds little robust evidence that buying the dip generates abnormal returns once risk and costs are considered.

7.1.5 Sector concentration and performance

To connect Finnes' stock selection to his sector choices, we aggregate all trades to the sector level and compute both the number of transactions and the net result in NOK for each sector. This provides a view of how his trading effort is distributed across sectors and how much each sector contributes to his realized performance.

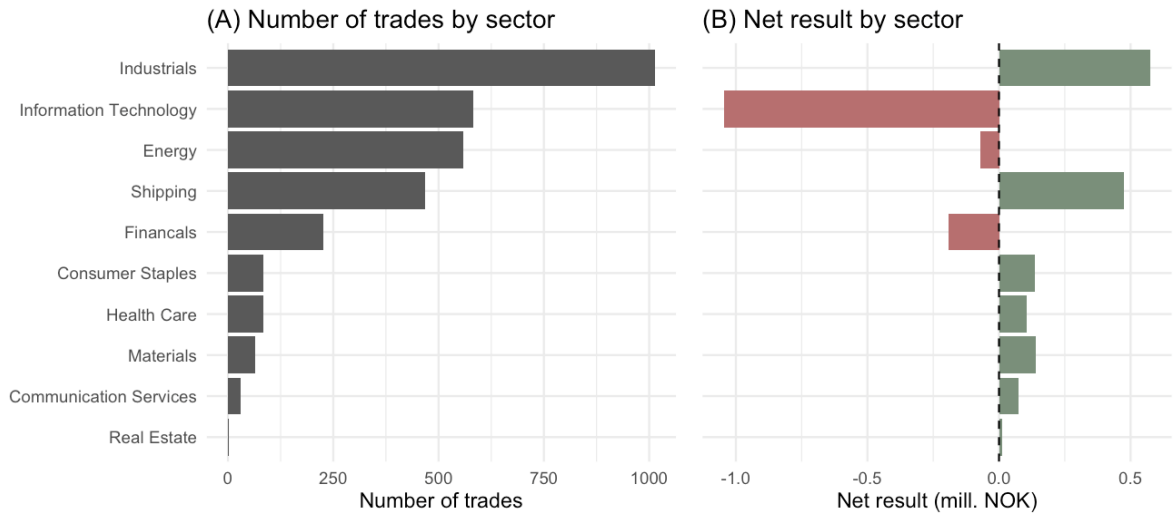


Figure 9: Trading activity (Panel A) and net result (Panel B) by sector.

At the sector level, the evidence points to a systematic misallocation of trading effort (Figure 9). The sectors that absorb many of his trades are loss-making, while sectors in which he trades only sporadically account for nearly half the net profit. The portfolio's positive outcome is thus driven by marginal parts of his opportunity set, whereas the segments he repeatedly engages with destroy value on a net basis.

One intensively traded sector stands out as a persistent loss center (Figure 9), with cumulative negative contributions that almost offset the gains generated elsewhere. This indicates that Finnes does not scale activity in areas where realized stock selection has been strong but instead recycles capital into segments where his ex-post-performance is weakest. The pattern is consistent with the familiarity bias discussed in Section 3.4, where trading is concentrated in familiar and salient sectors rather than in those where he has historically added value. In combination with the earlier evidence on overtrading and post-trade CAR, the sector results suggest a systematic disconnect between conviction, trading intensity and realized performance.

8. Conclusion

Our analysis of Sindre Finnes' trading shows a pattern typical of retail investors. Once we adjust for risk with the Carhart four-factor model, his alpha is slightly negative and not statistically different from zero, while his beta is well above 1 and statistically significant. His portfolio does not earn more than we would expect from its market risk and factor exposures. A simple low-cost index investment would have given a smoother and higher return over the period.

His trading style is a central part of the story. Finnes turns over his portfolio many times per year and makes heavy use of leveraged products. Even under conservative assumptions about commission rates, this generates large transaction costs. Much of the gross profit he earns is absorbed by fees and product costs. For a retail investor without an information advantage, such high activity makes outperformance unlikely.

The event-study results suggest timing and behavior also work against him. On average, stocks he buys underperform the index, while stocks he sells continue to do well. He often trades after sharp price moves and tends to concentrate in a few sectors where he loses money, while more occasional positions contribute most of the profit. This pattern fits well with known behavioral biases such as the disposition effect, familiarity bias and "buy-the-dip" rather than with skillful stock picking.

For other investors, the lesson from the Finnes case is clear. High turnover, leverage and concentrated bets create excitement, but not necessarily better results. A broadly diversified, low-

cost portfolio held over time is still the most reliable way to match or beat the average investor. According to Robert Næss, Finnes may not have performed spectacularly badly compared to other retail investors (personal communication, November 14, 2025). Still, his trading remains broadly consistent with the efficient market hypothesis once risk and realistic frictions are taken into account.

8.1 Further research

Further research could analyze Finnes' trading alongside a broader sample of Norwegian retail investors. With access to trading records from banks or brokers, one could construct a matched sample of investors with a similar profile and compare turnover and CAR patterns across groups. This would show whether his behavior is an extreme outlier, and whether overtrading and "buy-the-dip" patterns are widespread.

A second direction would be to investigate his trading with richer market data. With intraday timestamps and full order-book quotes one could study Finnes' execution quality and choice of limit versus market orders, linking performance more directly to microstructure frictions. Finally, from a policy perspective, future work could study how the public disclosure of his trades affected market perceptions and trading in the affected stocks, providing broader lessons for transparency and regulation around politically exposed investors.

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10. Appendix

Appendix A.1 Interview with Robert Næss (Nordea) - *November 14, 2025*

What is your current position and responsibilities, and briefly outline your professional background in Norwegian Equity Markets?

I have worked with equities for just over… I probably started in the stock market when I graduated in 1990, then I worked with equity for a couple of years. Since 1994 I have been in asset management, for just over 30 years. The last 20 years I have been at Nordea, both as a manager of global equity funds and of Norwegian equity funds.

Could you briefly outline also the analytical framework you apply when evaluating whether an individual investor outperforms a benchmark such as OSEBX?

We have actually managed to do that. So a fund that I was given responsibility for just over 20 years ago, which was called Norge Verdi, I can share the screen now so you can see. I have to mention this since my son who lectures likes to say that we never beat the index, so then I can show the fund that I manage. It is the only fund I manage, it is directly in Norwegian equities. You can see that over the last 20 years we have a 600% return, to clients after costs. You will avoid the fee that we charge as a fund, but then there will be other trading costs directly. And then of course it depends on which time period, but historically speaking it has not been very good. They tend to throw themselves onto trends, as you saw during the green wave, they are probably a bit too trigger-happy. They are a bit too fond of either trading too much or trying to find stocks that are so fantastically good, but then they end up finding bad companies.

You became widely interviewed by a handful of media outlets after the revelations of Sindre Finnes' trades, how would you describe his trading and trading pattern?

Yes, very active, a lot of trades. Even though I work full-time with this, when it comes to changes in positions he has been significantly more active than I and the team here have been. You can say that he is small and does not move the market that much, but it is really hard to understand why if you sit alone and have less information than we do, fewer opportunities to do analysis since you have a job on the side. Then it takes a lot for you to have an information advantage or a

competence advantage, so therefore it is hard to see that you are going to do that well and when you go through the research literature and look at what private investors who trade actively do, the results are consistently weak.

Finnes' had an unusually high activity across many stocks, from a professional perspective, what does that frequency typically signal about an investor's process?

First of all, there are many who basically see equities as trading, and then they think that is what creates value. And that is wrong. When you make the trades you can say: when you make an investment decision you can have good luck and bad luck. So therefore it is easy to give examples where monkeys are just as good as us portfolio managers. It is hard to beat the market. It is also hard to do badly over time, except in a way, and that is trades. With too much costs when you trade, you are almost guaranteed to do badly. So therefore, trading in a sensible way, not trading too much and being aware of costs – that is kind of the first thing for a manager. And there we see that retail investors are often not that good at it. Sindre Finnes, when he trades more than our team, we are six people with relevant backgrounds, long experience, good education and we have a lot of information systems, we have the opportunity to talk with management. And when he makes more decisions than we do, it is really hard to see why he should have much more competence than us with so many more resources. It is hard to see. This applies to him and others who trade actively. As long as you do not have a very special strategy, that you can somehow trade on the bid-ask spread and have a special strategy, but just blindly investing as he does, that is… You should not be able to beat the market then; when you trade a lot you should not achieve good results.

Finnes used a lot of leverage, especially when short-selling, what does that instrument choice suggest to you?

He had a lot of derivatives, right, and derivatives are the most expensive instruments you can buy. Right, leveraged instruments, OBX x4, x5. You do not see it directly, but it pays a lot to the brokerage house that makes these products. And then, again, when you incur that many costs, you have to be incredibly skilled not to spill money on it. I actually think, as you also mentioned, that he has done worse than the Oslo Stock Exchange index. He would have earned much more if he

had bought an index fund. On the other hand, if you compare him to others who trade actively, then he has probably done okay, probably better on average than the others who trade wildly.

In previous interviews you have remarked that Finnes trading must have extremely time required. In your experience, when does activity stop adding value and start destroying it?

I don't think there is a specific number. I think it depends on what you do. You see those who trade on information advantages, these big traders who trade in tiny volumes, because they manage to analyze a bid-ask spread and a little bit in advance. They can do an insane number of trades and make money from it. But of course, a private person who does not have that, but just trades based on what they assume is knowledge, then it is really the case that the more you trade, the worse it gets. If you just look 20 years back: OK, Olav Thon, they can work, so I just buy shares there, right, then you really have no disadvantage compared to us. The more often you trade, the more often you change decisions, the more the disadvantages come out.

In an interview with NRK, you revealed calculations that he would have made 60% more or NOK 1.1 million more if he had bought standard index funds, what do you think is the main reason why people don't buy index funds and follow general marked rules?

People love to… It is a bit like the lottery effect, and then the dream of really buying a share that rises a lot, you can brag about it and the feeling is very good, and most people have a pull towards trading, a bit like betting on the lottery or football betting or similar, so it is a human inclination that very many people like it.

Finnes took out a loan of 1.1 million kroner to finance these share trades. What does that say to you?

It says it is an investor who thinks it is fun to trade. And then it is probably the excitement around it that does it, with that, yes, with that inclination that people like risk and like gambling

Previously you have also said that Finnes "has not hit remarkably well." In intuitive terms, what would hitting well look like in the data? How far from that did this pattern appear?

Well, he has not done well compared to if he had bought a bit of all the shares on Oslo Stock Exchange blindly and sat on them. So in that sense he has not done well. But it has not been, like, if you take the average of overly eager people who like to trade, then he has probably done at least as well as the average, probably better. So it is not that he has done spectacularly badly, that is not it. It is really more that… his problem is that he trades actively, and if you have an information disadvantage, which they think he has, then you should lose money relative to the market, and that he has done.

If an active retail investor insisted on trading this often, what three simple guardrails would you impose (position sizing, liquidity thresholds, holding-period minimums, order type)?

First and foremost, before I start trading I would force myself to answer the question: where do I have an information advantage, what is my strength compared to Robert Næss'. So you have to be able to define where, as a trader, you have an edge. If you realize: OK, they know more than me, they have more information than me so I cannot beat them. Then you should not be able to beat the index, so you have to find a way. But it does not have to be impossible. In fact, one strategy that sounds a bit trainee-like, which actually is not that bad, is the "bellwethers" in Finansavisen. It is updated regularly with what changes they have made, so you follow their largest positions, not the small stuff, and then you actually have an edge over us. And that can be a perfectly fine strategy, because then you actually have an advantage over us. Even if I thought it was a good strategy, I could not have done it with the size of my portfolio, but a small investor can do it. So then a small investor can say: I actually have no clue about investing, but I think this and that investor is good so I just copy them. Then I can buy and sell them without moving the market. Or that you work in a sector and you think, with more insight than others, then that can also be. But you must at least define where you have your strengths, and believe that you are better than the others in the market. And then you can trade.

Finally, what's the single fairest sentence to summarize this case from a market-analysis standpoint?

It basically just shows that increased, heavy trading, if you check the international research literature, gives consistently poor results. So it shows that trading often is really something you should avoid.

And I can just add: it may have cost Erna and Høyre the election. And that is, in a way, a bit fascinating. It is just a hobby that is a bit poor, it is not as if you have ruined the Norwegian nation. But that is another matter.

Appendix B.1 Data construction and daily returns

Implementation in R

```
> # 1. Net daily order flow per ticker
  orders_daily <- trades %>%
      mutate(side_num = if_else(Side == "BUY", 1, -1),
             flow     = side_num * Quantity) %>%
      group_by(Ticker, Date) %>%
      summarise(flow = sum(flow), .groups = "drop")

  # 2. Cumulative raw positions and implied initial holdings
  positions_raw <- orders_daily %>%
      arrange(Ticker, Date) %>%
      group_by(Ticker) %>%
      mutate(Q_raw = cumsum(flow),
             min_Q = min(Q_raw),
             Q_adj = Q_raw - pmin(min_Q, 0)) %>%   # shift up if min_Q < 0
      ungroup()

  # 3. Merge with prices and compute daily stock returns
  prices <- prices %>%
      arrange(Ticker, Date) %>%
      group_by(Ticker) %>%
      mutate(R_it = P / lag(P) - 1) %>%
      ungroup()

  # 4. Start-of-day positions and portfolio return
  portfolio_daily <- positions_raw %>%
      left_join(prices, by = c("Ticker", "Date")) %>%
      group_by(Ticker) %>%
      arrange(Date) %>%
      mutate(Q_start = lag(Q_adj)) %>%
      ungroup() %>%
      filter(!is.na(Q_start)) %>%
      group_by(Date) %>%
      summarise(
          V_t   = sum(Q_start * lag(P)),      # start-of-day value
          R_pt  = sum(Q_start * lag(P) * R_it) / V_t)
```

The script above aggregates all trades to a net daily order flow per ticker, constructs an implied non-negative position path, and then merges these positions with daily prices to compute stock returns. The final object, “portfolio_daily”, contains one observation per trading day with start-of-day portfolio value and daily portfolio return. These daily returns are later compounded to monthly returns for the Carhart four-factor regression.

Appendix C.2 Carhart four-factor model

Model overview

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1\left(R_{M,t} - R_{f,t}\right) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 PR1YR_t + \varepsilon_{i,t} \qquad (5.1)$$

Equation 5.1: Carhart four-factor model

Where:

$R_{i,t} = Total\ return\ on\ stock\ or\ portfolio\ i\ at\ time\ t$

$R_{f,t} = Risk - free\ rate\ at\ time\ t$

$R_{M,t} = Total\ market\ portfolio\ return\ at\ time\ t$

$R_{i,t} - R_{f,t} = Excess\ return\ on\ stock\ or\ portfolio\ at\ time\ t$

$R_{M,t} - R_{f,t} = Excess\ return\ on\ the\ market\ portfolio\ (index)$

$SMB\ (Small\ minus\ big)$ is a measure of the difference in returns between small and large stocks

$HML\ (High\ minus\ low)$ is a measure of the spread of returns between the highest and lowest performing stock in each portfolio.

$PR1YR$ is a measure of the return spread between recent winners and losers, computed From performance over the past 12 month, excluding the most recent month. This factor is also mentioned as UMD, or momentum, throughout the text. The original notation by Carhart in his research paper was "PR1YR", but in recent years, the notations UMD or MOM has been more widely used in articles.

$\alpha_i = Abnormal\ return\ (intercept)\ for\ i\ after\ controlling\ for\ the\ factors$

$\beta_{1,2,3,4} = Factor\ coefficients$

$\varepsilon_{i,t} = Error\ term$

The model is estimated by ordinary least squares (OLS) over all months for our dataset. The intercept α measures whether Finnes outperforms a passive, risk-adjusted benchmark. A positive and statistically significant alpha would indicate that he beats the market given his exposure to systematic risk.

Implementation in R

```r
## 1. Monthly portfolio returns
portfolio_monthly <- portfolio_daily %>%
    mutate(YearMonth = format(Date, "%Y-%m")) %>%
    group_by(YearMonth) %>%
    summarise(
        R_p = prod(1 + R_pt) - 1,
        .groups = "drop")

## 2. Read Norwegian factor data (Ødegaard)
mkt     <- read_csv("Norway_market_portfolios_monthly.csv")   # contains R_M and date
factors <- read_csv("Norway_pricing_factors_monthly.csv")     # contains SMB, HML, UMD
rf      <- read_csv("Norway_Rf_monthly.csv")                  # contains R_f

## 3. Merge portfolio returns with factors
data_carhart <- portfolio_monthly %>%
    left_join(mkt,     by = "YearMonth") %>%
    left_join(factors, by = "YearMonth") %>%
    left_join(rf,      by = "YearMonth") %>%
    mutate(
        excess_port = R_p  - R_f,
        excess_mkt  = R_M  - R_f
    ) %>%
    filter(complete.cases(excess_port, excess_mkt, SMB, HML, UMD))

## 4. Estimate Carhart four-factor model
carhart_mod <- lm(excess_port ~ excess_mkt + SMB + HML + UMD,
                  data = data_carhart)
```

Results:

```
Call:
lm(formula = excess_port ~ excess_mkt + SMB + HML + UMD, data = data_carhart)

Residuals:
     Min       1Q   Median       3Q      Max
-0.16333 -0.04788 -0.01441  0.02215  0.93066

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.003666   0.012829  -0.286    0.776
excess_mkt   1.378893   0.304445   4.529  1.6e-05 ***
SMB          0.342524   0.307513   1.114    0.268
HML         -0.186581   0.204284  -0.913    0.363
UMD         -0.041875   0.197578  -0.212    0.833
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1183 on 103 degrees of freedom
Multiple R-squared:   0.22,     Adjusted R-squared:  0.1897
F-statistic: 7.264 on 4 and 103 DF,  p-value: 3.413e-05
```