ANCHORING BIAS IN SWEDISH EQUITY MARKETS

AN EMPIRICAL STUDY ON THE INFLUENCE OF PAST FUNDAMENTALS ON INVESTOR EXPECTATIONS

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Abstract:

This paper investigates whether deviations of accounting fundamentals from their previous means predict future equity returns in the cross-section. We construct a variable termed performance deviation index (*PDI*) based on deviations of seven accounting variables against their rolling means. Through cross-sectional regressions and analysis of *PDI*-based long-short portfolios, we find that *PDI* demonstrates significant return predictability in the short term. In addition, we find that the performance of *PDI*-based portfolios is primarily attributed to the short leg. Furthermore, our research reveals a negative relationship between firm size and the return predictability of *PDI*, indicating an increased performance in predicting returns for small-cap firms.

Keywords:

PDI, anchoring bias, stock return predictability, accounting variables

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1. Introduction

This thesis aims to assess how deviations in quarterly fundamental accounting items from their preceding means predict Swedish stock market returns in excess of other established predictors, including the Fama-French-Carhart four factors.

The thesis surrounds the psychological phenomena and cognitive bias of anchoring, where individuals form assessments and conclusions too heavily based on readily obtainable, and often irrelevant, initial information (Tversky & Kahneman, 1974). An example of this is that forecasts of macroeconomic quantities made by industry experts are systematically biased towards their incremental past values (Campbell & Sharpe, 2009). A possible sequel to this result would be that investors anchor their investment decisions on long-run averages of firm fundamentals, which constitutes the main premise of investigation in this thesis. For instance, consider an investor that is anchored to the long-run average of a company's profitability. This anchoring would imply that the investor will not adjust their future expectations enough when significant news causes a substantial change in profitability. This hypothesis has also been explored in earlier research, for example by Avramov et al. (2020).

To capture this anchoring bias, we draw inspiration from Avramov et al. (2020) and define a performance deviation index (PDI, henceforth) based on quarterly deviations compared to the rolling mean of the preceding three quarters in seven fundamental accounting items reflecting operational performance. Unlike Avramov et al. (2020), and to our understanding any other published papers, we study Swedish market data instead of US based companies, hence offering an extension to their proposed theory and our own discussion as to why this performance deviation metric yields overperformance in the studied data.

Our findings reveal that PDI exhibits significant return predictability in the short term, with significant coefficients in cross-sectional regressions against unadjusted returns as well as returns adjusted against Fama-French-Carhart factors while also including a selection of control variables. Additionally, in contrast to Avramov et al. (2020) we observe that the performance of PDI-based long-short portfolios is primarily driven by the performance of the short leg. Moreover, our analysis demonstrates a negative relationship between firm size and the return predictability of PDI, indicating a higher performance of PDI for small-cap firms. These findings offer insights into the effectiveness and limitations of PDI as a return predictor, highlighting its potential for generating alpha in the Swedish stock market while considering factors such as time horizons and firms size dynamics.

2. Previous research

Avramov et al. (2020) find that quarterly deviations in fundamental accounting items, such as operating income, retained earnings and sales, from their preceding averages strongly predict future stock market returns. Utilizing the deviation-based measures yields return predictability that exceeds anomalies such as earnings drift, profitability and 52-week highs. The model generates statistically significant alphas while considering Fama-French factors and standard momentum, as well as when applying value weighting, excluding microcap stocks, and taking into account transaction costs. They ascribe the predictive ability of the deviations to the psychological bias of anchoring, arguing that investors are anchored to past means of fundamental items, causing them to underact to large deviations from their established anchor which generates a lag in stock price development.

Avramov et al. (2020), as well as this thesis, share resemblances with a broad literature universe of accounting-based stock return predictors. Asness et al. (2017) creates a Quality Minus Junk (QMJ) factor that goes long high-quality stocks and shorts low-quality stocks to predict significant risk-adjusted returns. The quality of a stock is determined by four factors: profitability, growth, safety, and dividends, i.e. a high-quality stock is profitable and growing, exhibits a low required return and pays a high fraction of profits out to shareholders. The stocks are then divided into hierarchies to capture the spread in returns between high-quality and low-quality stocks, with the long-short portfolio later being rebalanced periodically to maintain desired exposure to the QMJ factor. Asness et al. (2017) conclude that the constructed QMJ factor exhibits a significant return premium over the long term.

Ball et al. (2016) examines the relationship between fundamentally underpinned accounting measures with stock returns. They argue that companies characterized by low accruals, high cash flows, and strong operating profitability signals higher earnings quality and overall better financial health, and are expected to generate higher stock market returns than less sound peers. The paper concludes that this theory holds true, and that firms with higher-quality earnings characteristics tend to outperform those with lower-quality earnings characteristics.

Similarly, Fama & French (2006) investigates the relationship between profitability and equity market returns. The study uses profitability ratios, such as operating income and gross profit divided by a company’s assets, to identify companies with strong fundamental accounting characteristics. The paper concludes that companies with higher profitability on average yield higher returns compared to peers with lower profitability, even when controlling for other factors such as size and book-to-market.

Further, Avramov et al. (2020) and this paper also find behavioral explanations to the predictability of fundamental accounting measures, a subject that has a rich history of previous research.

Ball & Brown (1968) first investigated the phenomenon of “Post-Earnings Announcement Drift” (PEAD) and its relation to earnings information asymmetry. They studied how equity markets react to earnings announcements and to what extent this information is incorporated into stock prices immediately versus following a delayed adjustment period. They find that following an earnings announcement surprise, stock prices tend to drift in the direction of the earnings announcement, and that the information is not priced in by the market immediately following the information being available. Thus concluding that investors on average tend to underreact to earnings announcement information. The PEAD phenomenon Ball and Brown attribute to earnings information asymmetry, proposing that certain investors, such as institutional, insiders and analysts, may possess superior information about a company’s earnings performance before it is publicly announced to the market. This information advantage consequently allows mentioned investors to envision the true value of the earnings surprise before it is fully captured by the market. They argue that outside investors may take longer to process earnings information, leading to a persistence in the PEAD beyond the initial announcement period and an extended stock price adjustment interval. This implying that investors who are able to exploit this information asymmetry and ride the drift following an earnings announcement surprise to reap superior returns.

Barberis et al. (1998) look into how investor sentiment driven by psychological biases, such as representativeness bias, affect stock prices. They argue that investors form expectations based on fundamental information, but also on sentiment underpinned perceptions. This occurrence can lead to predictable patterns in stock prices, including overreaction and underreaction to new information accessible to the market.

Cen et al. (2013) investigates the impact of anchoring bias on the equity market by analyzing how analysts’ earnings forecasts and the companies’ subsequent stock returns are influenced by named bias. They find that anchoring bias leads analysts to rely excessively on initial and antecedent information when conducting their research reports and financial predictions. They explain a tendency for analysts to adjust estimates away from an initial anchor as time passes, i.e., drift, but conclude that this drift effect does not fully capture the anchoring bias and that their predictions remain influenced by the anchor. This leads investors to underreact to news, where new information is not immediately priced in but instead causes the stock price to drift upwards as a reaction to positive news, and vice versa for negative news. This, they argue, thereafter contributes to predictable patterns in stock returns and that investors can acknowledge and leverage this anchoring bias to deliver outperforming returns.

Additional papers that investigates psychological biases effect on stock market returns include Daniel et al. (1998) who explores the impact of psychological biases such as overconfidence and representativeness on underreactions and overreactions on new market information. Barberis & Huang (2001) who explores the concept of mental accounting and suggests that investors tend to mentally account for gains and losses separately, influencing stock market returns. Similarly, Shefrin & Statman (2000) constructs a model that derives optimal portfolio choice combining prospect theory and mental accounting with traditional preferences.

To conclude, there exists a plethora of studies that aim to unravel the hypothesis that one can decipher fundamentally sound companies from bad ones using accounting measurements, and with that insight predict future stock market outperformance. In addition, psychological biases and their effect on equity markets also exhibit a great library of research. This in conjunction establishes the concept that equity markets are structurally inefficient in the sense that information is overlooked, partially due to behavioral biases, creating investment opportunities that are not priced away. This thesis aims to distinguish such an investment opportunity by utilizing the anchoring bias.

3. Data and Methodology

3.1. Scope of Research

This study considers all Swedish firms listed on the Nasdaq Stockholm main market (i.e., excluding firms listed on First North and First North Premier). As per March 2024, this encompasses 393 firms in total. Note that we have not been able to include delisted firms in our sample, which could have some implications with regards to survivorship bias. Our sample period encompasses January 1994 – December 2023. In total, we have 51,598 firm-month observation in the full sample period.

For regressions conducted on returns adjusted for Fama-French-Carhart four factors, the sample period ends in December 2019, as the source does not provide Swedish factor premiums beyond that.

3.2. Data Sources

To conduct this study, we most importantly require data on stock prices as well as quarterly firm fundamentals required to construct the *PDI* variable and our control variables. We obtain both stock prices and firm fundamentals from the S&P Capital IQ database. To prevent look-ahead bias, we match firm fundamentals with corresponding returns according to the filing dates of the quarterly reports, which makes sure that the financial information is publicly available for investors at each time point. If the exact release date of the quarterly report is unavailable, we assume a 60-day release period from the end of each quarter, similar to Avramov et al. (2020).

Data for the Fama-French-Carhart four factors for the Swedish stock market are obtained from Swedish House of Finance National Research Data Center, which also includes estimates of Swedish risk-free interest rates. The factors are estimated for 1983–2019. We choose to utilize Swedish factors to capture country-specific risk premiums for each factor. Griffin (2002) as well as a later study done by Fama and French (2012) show that the Fama-French factors are regional or country-specific, such that local factors provide a better explanation of time-series variation in stock returns than global factors. The above mentioned factors also include an estimate of market return (R_m), which is the SIX Return Index, that is a value-weighted index of all stocks listed at the Stockholm Stock Exchange and includes reinvested dividends.

3.3. PDI Variable

A centerpiece of our study is constructing a variable that measures the deviation of firm fundamentals against previous means. Similar to Avramov et al. (2020) we construct a composite measure called Performance Deviation Index, consisting of deviations of seven financial metrics from their preceding means. The seven metrics are related to firms' operational performance, consisting of: *(i) Cash and short-term investments, (ii) retained earnings, (iii) operating income, (iv) sales, (v) capital expenditures, (vi) invested capital and (vii) inventories.* As mentioned by Avramov et al. (2020), this set of variables are used to capture overall managerial efficiency by considering measures of generated and accumulated income, financial health, capital investment, and buildup of inventory.

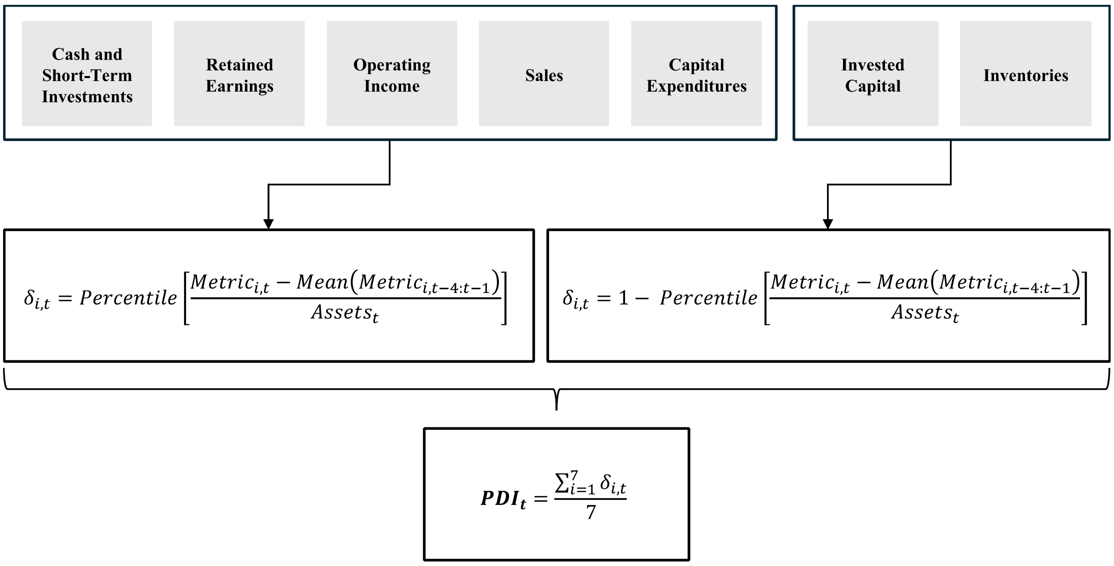
More specifically, *PDI* is constructed as follows:

1) For each of the seven operating metrics, we calculate the deviation between the most recent quarterly release and the average of over the preceding three quarters.
2) Deviations are then scaled by total assets to standardize deviations across firms of different sizes.
3) Each deviation is then assigned a percentile value relative to all stocks' deviations during the same period. For *invested capital* and *inventories* we assign a value of one minus the percentile value (to represent an expected negative relationship).
4) All seven percentile values are equal weighted to form the composite measure *PDI*.

In Figure 1 we visually illustrate the step-by-step calculation of the *PDI* variable:

Figure 1. PDI variable calculation

The figure illustrates how the PDI variable is constructed, for each firm, from seven financial metrics. "Percentile" refers to assigning a percentile rank (0-1 or 0-100%) which represents the fraction of firms that have lower deviation values in metric $\boldsymbol{i}$ *in the cross-section at time* $\boldsymbol{t}$*.* $\boldsymbol{\delta_{i,t}}$ *denotes the percentile value calculated for financial metric* $\boldsymbol{i}$ *at time (month)* $\boldsymbol{t}$ *for a certain firm. The PDI variable for a certain stock at time* $\boldsymbol{t}$ *therefore refers to the equal weighted mean of all seven* $\boldsymbol{\delta_{i,t}}$ *calculated from the seven financial metrics.*



3.4. Control Variables

In our regressions throughout the paper, we include a selection of six control variables from different categories to ensure that the return predictability of *PDI* is explained by already well-established predictors or characteristics. Our selection is a subset of the control variables used by Avramov et al. (2020) covering conventional firm characteristics, price momentum, accounting fundamentals and limits to arbitrage.

- The first two control variables are conventional firm characteristics - Market Value of Equity (*ME*) accounts for the negative relationship between size and returns (Banz, 1981; Fama & French, 1992), and Book-to-Market (BE/ME) controls for the well-established value vs. growth firm return differential. Note that we use the logarithm of *ME* to standardize the size of the coefficient.
- We include Return over months -12 to -2 (*MOM*) controls for short-term momentum. Jegadeesh and Titman (1993) found that stocks with high returns over the past 3-12 months tend to outperform in the future. We use the same past return window as Avramov et al. (2020) to increase replicability.
- We include two accounting-based variables – Return on Assets (*ROA*) and Return on Equity (*ROE*), which are prominent firm performance metrics. Chen, Novy-Marx, and Zhang (2011) find a positive relationship between *ROE* and future stock returns.
- The last control variable accounts for limits to arbitrage – Turnover (*TURN*), defined as the ratio between trading volume and shares outstanding. Datar, Naik, and Radcliffe (1998) find that liquidity plays a significant role in explaining cross-sectional variations in stock returns. While Turnover may not capture all aspects of liquidity comprehensively, it serves as a gauge of market activity and participation. Turnover may not fully capture the depth and resilience of a market, as it can be influenced by factors such as speculative trading or market sentiment, rather than genuine liquidity. Despite these limitations, Turnover remains widely used in research due to its accessibility and insight into market dynamics. Besides using Turnover as a control variable, it is frequently used to gauge whether a strategy is implementable in practice, with regards to liquidity or limits to arbitrage.

3.5. Descriptive statistics

In this section, we provide descriptive statistics for the PDI variable and our control variables. These statistics aid in understanding the distributional characteristics and interrelations among the variables under examination.

Table 1. Descriptive Statistics

This table displays descriptive statistics for the PDI variable and our control variables. For each variable, the table reports mean, standard deviation and correlation against PDI. The sample period is between January 1994 – December 2023. The panel data for each variable is vectorized to calculate means, standard deviations, and correlations.

Variable	**Mean**	**Standard Deviation**	**Correlation with *PDI***
PDI	0.501	0.112	1.00
Log Size (*ME*)	8.264	2.026	0.071
Book-to-Market (*BE/ME*)	0.594	0.921	-0.036
Return over months -12 to -2 (*MOM*)	0.117	0.888	0.080
Return on Assets (*ROA*)	0.032	0.122	0.320
Return on Equity (*ROE*)	-0.038	3.017	0.041
Turnover (*TURN*)	0.049	0.112	-0.002

As seen from Table 1**,** most of the correlations between the control variables and PDI are close to zero. Return on Assets (ROA) has the highest correlation with PDI at 0.32, and all other correlations are below 0.1. Therefore, this indicates that the PDI variable is distinct from other examined predictors.

4. Empirical Analysis

4.1. Cross-Sectional Regressions

This section investigates the relationship between *PDI* and the cross-section of future stock returns. To assess the *PDI*-return relationship, we utilize a Fama MacBeth (1973) cross-sectional regression setup, where we compute regressions for each cross-section (month), and report the average slope coefficients of all monthly regressions. The Fama Macbeth procedure allows us to estimate consistent standard errors in presence of cross-sectional correlation in panel data. As delisted firms are not included in our sample, observations are sparser in earlier cross-sections of the sample. Furthermore, the Fama Macbeth procedure applies an equal weighted average across all cross-sectional regressions, effectively giving early cross-sections equal weighting as later cross-sections with more observations. Therefore, to guarantee robustness of regressions within each cross-section, we filter our panel data using a criterion of at least 30 firms within each cross-section (which roughly filters out cross-sections before October 2000 due to sparse data) for all our regressions.

First, we present results from regressing raw returns against *PDI*, both including and excluding control variables (see section 3.4). Next, we move on to regressing Fama-French-Carhart adjusted returns as well as market adjusted returns against *PDI*.

The Fama-French-Carhart model includes the three Fama-French factors market, size (SMB) and value (HML) factors, along with the UMD momentum factor proposed by Mark Carhart. By adjusting returns for the Fama-French-Carhart four factors, we can test the return predictability of PDI beyond what is explained by exposure to these established factors. To adjust returns for the Fama-French-Carhart factors, we first calculate each firm's factor loading (β) on the four factors through time-series regressions (see *Appendix B2* for our factor loadings distribution). Then, we calculate expected returns for each firm over the entire sample period, based on the estimated factor loadings. After that, the expected returns according to the fitted model are deducted from actual returns to obtain alpha (α) or returns adjusted for Fama-French-Carhart factors. The sample period for cross-sectional regressions against Fama-French-Carhart adjusted returns ends in December 2019, as our source does not provide Swedish factor premiums beyond that

Inherent in adjusting returns according to a fitted model using factor loadings estimated from historical data, there is a potential look-ahead bias. We use historical data over the entire sample period to estimate factor loadings and alpha, of which some of the information in this estimation would not have been available at the time of the prediction. In addition, by estimating one set of factor loadings using the entire sample period, we have not factored in the possibility that Fama-French-Carhart factor loadings might change over time. Therefore, to construct an analysis that is robust from above mentioned issues, we also include regressions of *PDI* against market adjusted returns ($R_i – R_m$). For each security return at time *t*, denoted R_i we deduct the market returns to obtain excess returns against the market. Effectively, this is equivalent to adjusting returns to the market factor with the assumption that all securities have a market beta (β) of 1. This provides a simpler model free from assumptions, while still providing a way of adjusting returns for the market factor. Note that our market returns are obtained from the SIX Return Index (see section 3.2).

Table 2 presents an overview of our regressions of raw returns, Fama-French-Carhart adjusted returns, and market adjusted returns against PDI. For full regression results, refer to *Appendix B1-B4*.

Table 2. Summary of cross-sectional regressions of returns against PDI

This table summarizes average slope coefficients and corresponding t-values (in parentheses) from monthly cross-sectional regressions of: (Panel A) Raw returns against PDI and control variables, (Panel B) Raw returns against PDI excluding control variables, (Panel C) Fama-French-Carhart adjusted returns against PDI and control variables, (Panel D) Market adjusted returns against PDI and control variables. We report results for returns over (i) next month, (ii) months 2-6, (iii) months 7-12, (iv) months 13-24. Dependent variables (returns) are computed in percentage points while predictors are computed in decimal form. So, coefficients are interpreted as the percentage points change in returns from one unit change in the predictor.

Panel A: Raw Returns – Full Regressions

	Dependent variable:			
	R_{t+1}	$R_{t+2:t+6}$	$R_{t+7:t+12}$	$R_{t+13:t+24}$
PDI	2.90^{***}	4.70^{***}	4.00^{**}	0.32
	(3.50)	(3.20)	(2.10)	(0.09)

Note: *p<0.1; **p<0.05; ***p<0.01

Panel B: Raw Returns – Without Control Variables

	Dependent variable:			
	R_{t+1}	$R_{t+2:t+6}$	$R_{t+7:t+12}$	$R_{t+13:t+24}$
PDI	4.10^{***}	6.60^{***}	4.60^{***}	-2.30
	(5.30)	(4.90)	(2.60)	(-0.60)

Note: *p<0.1; **p<0.05; ***p<0.01

Panel C: Fama-French-Carhart Adjusted Returns

	Dependent variable:			
	Adj. R_{t+1}	***Adj.*** $R_{t+2:t+6}$	***Adj.*** $R_{t+7:t+12}$	***Adj.*** $R_{t+13:t+24}$
PDI	3.60^{***}	5.10^{**}	4.40^{*}	-2.10
	(3.90)	(2.50)	(1.70)	(-0.54)

Note: *p<0.1; **p<0.05; ***p<0.01

Panel D: Market Adjusted Returns

	Dependent variable:			
	$(R_i - R_m)_{t+1}$	$(R_i - R_m)_{t+2:t+6}$	$(R_i - R_m)_{t+7:t+12}$	$(R_i - R_m)_{t+13:t+24}$
PDI	3.50^{***}	6.20^{**}	7.20^{**}	-4.00
	(3.20)	(2.50)	(2.50)	(-1.00)

Note: *p<0.1; **p<0.05; ***p<0.01

For cross-sectional regressions against raw returns including control variables, we find that the *PDI* coefficient is highly significant for predicting next month returns, and returns between months 2-6, with coefficients of 2.90% (t = 3.50) and 4.70% (t = 3.20) respectively. However, contrary to Avramov et al. (2020), we find that the cross-sectional predictability attenuates for longer time horizons. The coefficient is still significant at 5% significance level for months 7-12 with a coefficient of 4.00% (t = 2.10) but becomes non-significant for months 13-24. Note that the size of coefficients cannot be compared between different time horizons, as returns in longer time horizons, such as for 13-24 months, refers to the compounded returns over the entire period. Instead, t-values should be used to compare the significance of the coefficients between different time horizons.

As expected, for our regression without any control variables, the *t-values* are higher across the first three-time horizons. However, the coefficient for months 13-24 is still non-significant, further supporting the view that the return predictability of *PDI* declines for longer time horizons.

After adjusting returns for the four Fama-French-Carhart factors, the significance of the *PDI* coefficient for next month returns is still large (3.60%) and highly significant (t = 3.90). We find that the coefficient for months 2-6 is now only significant at the 5% significance level, with t = 2.50, compared to previously being significant at 1% level. For the time horizons of months 7-12 and 13-24, we find weak significance (t = 1.70) and non-significant results respectively. Overall, the pattern of our results is consistent with the regressions on raw returns, where the significance of the coefficients attenuates for longer time horizons. As expected, we also find that the significance is slightly lower across the board, especially with lower significance for months 2-6 and months 7-12.

We find that the results of cross-sectional regressions of market adjusted returns ($R_i - R_m$) against *PDI* yield similar results as the Fama-French-Carhart regressions, which provides further support for the conclusions above. One difference is that the coefficient for months 7-12 is significant at 5% significance level.

All our cross-sectional regressions show non-significant results for the time horizon between months 13-24, which strongly indicates that the performance of *PDI* attenuates for longer time horizons.

4.2. *PDI*-based portfolios

4.2.1. Alphas of *PDI*-based zero-cost portfolios

To assess the profitability of a *PDI*-based portfolio, we form zero-cost strategies using the *PDI* variable. First, we organize firms within each cross-section into deciles based on *PDI*. We then form a strategy that takes a long position in stocks within the top *PDI* decile, and short position in stocks within the bottom *PDI* decile. By analyzing the payoffs of top-minus-bottom *PDI* portfolios, we can isolate the performance of *PDI* as a return predictor.

For payoffs of portfolio holding periods above one month, we utilize the rebalancing procedure advocated by Jegadeesh and Titman (1993). The procedure increases the power of our tests by including portfolios with overlapping holding periods. Suppose K denotes the portfolio holding period. At the beginning of each month t, securities are ranked into deciles based on *PDI*. The strategy takes a long position in the top decile, and short position in the bottom decile, and holds this position for K months. This implies that in the next month, the strategy will still be invested in the portfolio formed one month earlier, in addition to forming a new portfolio based on new decile rankings. Jegadeesh and Titman (1993) proposes a rebalancing procedure that equally weighs returns of portfolios with different time horizons. Effectively, this means that in any given month t, the strategy will equal weigh a set of portfolios that are constructed in the current month, as well as in the previous $K - 1$ months. Every month, the strategy closes out the position initiated in $t - K$, and $1/K$ of the securities in the entire portfolio is revised. This rebalancing method allows us to analyze returns for longer holding periods while keeping the power of our tests high.

Table 3. Annual alphas of PDI-based zero-cost portfolios against Fama-French-Carhart four factors

This table summarizes annual alphas (in %) of PDI-based zero-cost portfolios for holding periods ranging between 1 to 24 months, and their significance (in parenthesis). The alphas are estimated against the four Fama-French-Carhart factors. We display results for both equal-weighted and value-weighted portfolios. Note that annual alphas are defined as monthly alphas multiplied by 12 (no compounding).

	Holding Period (months)					
	1	***3***	***6***	***12***	***18***	***24***
Equal-Weighted Portfolios	21.36***	16.80***	11.52***	5.64**	2.52	4.44**
	(4.20)	(3.68)	(2.89)	(1.86)	(0.99)	(1.97)
Value-Weighted Portfolios	15.48**	5.88	-0.48	0.00	-0.96	1.56
	(2.27)	(1.06)	(-0.12)	(-0.02)	(-0.40)	(0.66)

Note: *p<0.1; **p<0.05; ***p<0.01

As seen in Table 3, we find that alphas are significantly higher and more persistent for equal-weighted portfolios than value-weighted portfolios. For equal-weighted portfolios, the alphas are highly significant between holding periods of 1-6 months, with annual alphas ranging from 11.52% - 21.36% (*t*-values between 2.90 – 4.20). Similar to what was found for the cross-sectional regressions in Table 2, the performance of *PDI*-based portfolios declines for longer time horizons. We find that annual alphas are non-significant even for equal-weighted portfolios at a holding period of 18 months.

4.2.2. Decomposing performance of long and short leg

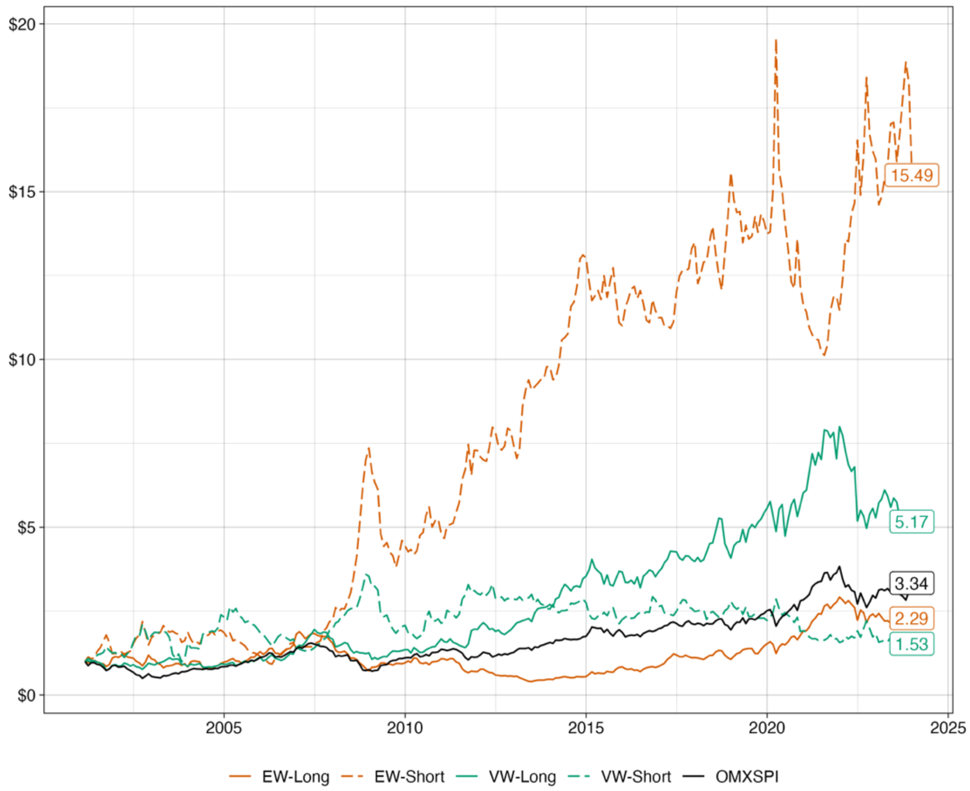
One noteworthy aspect of the findings of Avramov et al. (2020) is that the performance of the *PDI* variable is mostly attributable to the long leg of the long-short strategy, which stands in contrast to other studies such as Stambaugh, Yu and Yuan (2012) that shows that most anomalies largely derive their profitability from the short leg due to short-sale impediments.

We investigate the findings of Avramov et al. (2020) on Swedish data, by plotting the performance of the long and short legs of the *PDI*-based zero-cost strategy separately. As per our understanding, Avramov et al. (2020) only investigates this decomposition for value-weighted decile portfolios (i.e., where the securities in each decile are value-weighted), and find that the long leg significantly outperforms the short leg. We also include a plot for the long and short leg of equal weighted decile portfolios.

In Figure 2, we illustrate the returns of taking a long position in the top *PDI* decile, and short position in the bottom *PDI* decile, for both value-weighted and equal-weighted portfolios. We compare the long leg and short leg of the PDI-based zero-cost portfolios to a market proxy. We use OMX Stockholm PI (OMXSPI) as market proxy. OMXSPI is a value-weighted index of all shares listed on the Nasdaq Stockholm main market, so it fully corresponds to the stocks selected in our sample. The market proxy is also reindexed to start at $1 in January 2001. The observation period ends in December 2023. As explained previously, the long and short leg of the *PDI*-based strategy refers to a long position in the top PDI decile, and short position in the bottom PDI decile respectively. The returns below refer to portfolios with a one month holding period, so each month a new portfolio of stocks is selected based on *PDI*. "EW" denotes equal-weighted portfolios, and "VW" denotes value-weighted portfolios.

Figure 2. Performance of long and short legs of PDI-based zero-cost portfolios against OMXSPI

The figure illustrates the value of $1 invested at the end of January 2001 of a long position in the top PDI decile, and short position in the bottom PDI decile, compared to OMXSPI. The calculation is based on portfolios with monthly rebalancing. The long leg refers to a long position in the top PDI decile, and the short leg refers to a short position in the bottom PDI decile.



The graph indicates findings similar to Avramov et al. (2020) with regards to value-weighted portfolios. As seen in Figure 2, the long leg of the zero-cost strategy significantly outperforms the short leg for value-weighted decile portfolios. The short leg also underperforms in comparison to the market proxy. In December 2023, the long leg is valued at $5.17 compared to OMXSPI at $3.34, while the short leg is valued at $1.53. In general, short positions are expected to perform worse than the market proxy in bull markets due to negative market beta.

However, our analysis also uncovers an aspect that is unexplored by Avramov et al. (2020), relating to the performance of equal-weighted decile portfolios. For equal-weighted portfolios, the performance of the long and short legs is reversed. The short leg of the equal weighted portfolio ends up at a terminal value of $15.49, significantly outperforming the long leg at $2.29. The short leg of the equal-weighted portfolio also significantly outperforms the long leg of the value-weighted portfolio. This result significantly diverges from the findings of Avramov et al. (2020), where the long leg of the zero-cost strategy significantly outperformed the short leg.

Nevertheless, the plot in Figure 2 does not account for the risk exposures of the decile portfolios. All else equal, a riskier portfolio commands higher required returns. Therefore, to get a more comprehensive understanding of the observed performance of the long and short leg of the *PDI*-based portfolios, it is imperative to account for systematic risk exposure. In the next section, we investigate the risk profile of value-weighted and equal weighted top versus bottom *PDI*-based portfolios.

4.2.3. Properties of *PDI* portfolios

In Table 4, we compute standard deviations and Fama-French-Carhart factor loadings of top and bottom *PDI* deciles for both equal-weighted and value-weighted portfolios to investigate whether different risk exposures could explain differences in returns between the deciles. This approach allows us to disentangle the alpha generated by each leg of the portfolio from the systematic sources of risk captured by factors such as market risk, size, value, and momentum. We also provide average market cap, book-to-market, and turnover of the top and bottom PDI deciles. For average market cap, we provide both equal weighted (arithmetic) and value-weighted averages to gauge the differences in average portfolio market caps when using equal-weighted and value weighted portfolios.

Table 4. Risk and characteristics of PDI portfolios

The table reports risk measures and characteristics of the top PDI decile, bottom PDI decile, and top-minus-bottom portfolio (zero-cost portfolio). Panel A reports portfolio standard deviations (second column) and Fama-French-Carhart factor loadings for equal-weighted portfolios. Panel B reports the same measures for value-weighted portfolios. Coefficients and their t-values (in parenthesis) of factor loadings are obtained from regressing monthly excess returns of the portfolios against Fama-French-Carhart factors. The coefficients of the bottom deciles refer to the performance of the decile "as is" and does not refer to a short position in the decile. The top-minus-bottom refers to a long position in the top decile and short position in the bottom decile. For factor loadings, we include equal slopes t-tests to test whether the coefficients between top and bottom deciles are statistically different from each other (parentheses refers to t-values). Panel C reports average firm characteristics for top and bottom PDI deciles.

	Portfolio	**Fama-French-Carhart Four Factors**				
Portfolio	**Monthly STD**	**Intercept**	**Market**	**SMB**	**HML**	**UMD**
		Panel A: Equal -Weighted Portfolios				
Top Decile	6.56	-0.34	0.76***	0.70***	-0.11	0.04
		(-1.02)	(11.00)	(7.50)	(-1.11)	(0.88)
Bottom Decile	7.64	-2.23***	0.91***	0.78***	-0.17*	-0.05
		(-6.13)	(12.90)	(8.21)	(-1.68)	(-1.23)
(Equal Slopes *t*-test)		(5.19)	(-2.17)	(-0.88)	(0.60)	(2.12)
Top-minus-Bottom	5.75	1.78***	-0.15*	-0.08	0.06	0.09*
		(4.20)	(-1.76)	(-0.72)	(0.48)	(1.72)
		Panel B: Value -Weighted Portfolios				
Top Decile	6.16	0.11	0.74***	0.08	0.02	0.12***
		(0.35)	(11.10)	(0.85)	(0.25)	(2.86)
Bottom Decile	8.22	-1.18**	0.82***	0.27**	-0.18	-0.10*
		(-2.46)	(8.50)	(2.03)	(-1.30)	(-1.70)
(Equal Slopes *t*-test)		(3.15)	(-0.99)	(-1.69)	(1.71)	(4.27)
Top-minus-Bottom	7.97	1.29**	-0.08	-0.19	0.20	0.22***
		(2.27)	(-0.72)	(-1.22)	(1.24)	(3.08)

Note: *p<0.1; **p<0.05; ***p<0.01

Panel C: Characteristics of PDI portfolios:

Portfolio	**Equal-Weighted Average Market Cap (SEKm)**	**Value-Weighted Average Market Cap (SEKm)**	**BE/ME**	**TURN**
Top Decile	17,636	169,664	0.53	0.058
Bottom Decile	13,625	166,874	0.61	0.056

Comparing the monthly portfolio standard deviations of the top and bottom *PDI* deciles, the average standard deviation of the top *PDI* decile is slightly larger than the bottom portfolio for both equal-weighted and value-weighted portfolios, where the spreads are 1.08% and 2.06% for equal weighted and value weighted portfolios respectively. Looking at the magnitude of our standard deviation spreads, it is unlikely that the return predictability of *PDI* is explained by the low volatility anomaly (Baker & Haugen, 2012).

We find some minor differences in characteristics between top and bottom *PDI* deciles. Factor loadings on market are slightly higher for the *PDI* bottom decile than the top decile for both equal-weighted and value-weighted portfolios. Also, for both equal-weighted and value-weighted portfolios, the top decile loads positively on the momentum factor (*UMD*), while the bottom decile loads negatively on the momentum factor. The difference in momentum loadings is most significant for value-weighted portfolios, with a *t*-value of 4.27 in equal slopes *t*-test. For size (*SMB*) and value (*HML*), the differences between top and bottom deciles are non-significant. In addition, Panel C shows that the differences between deciles with regards to market cap, book-to-market and turnover are small.

We find larger differences in characteristics between equal-weighted and value-weighted *PDI* portfolios. As expected, equal-weighted portfolios load significantly higher on the size factor (*SMB*) for both top and bottom deciles, due to equal weighted portfolios having a relatively large weight on small cap stocks. This can also be seen in Panel C where the value-weighted average market caps of the top and bottom deciles are markedly larger than the equal-weighted averages. So, the average firm size in a value-weighted portfolio is significantly larger than an equal-weighted counterpart.

More importantly, by investigating alphas of each decile, we can derive the source of *PDI* alpha generation in more detail. On a stand-alone basis the bottom decile for equal-weighted portfolios has a highly significant alpha of -2.23% (it is negative but becomes positive when shorting). In addition, the bottom *PDI* decile for value-weighted portfolios also has a significant alpha at 5% significance level, at -1.18%. This indicates that the alpha generation of *PDI*-based zero cost portfolios primarily originates from the short leg. This finding differs from Avramov et al. (2020) who find that the alpha of *PDI* primarily stems from the long leg of the *PDI* based strategy. Specifically, as equal-weighted portfolios have higher weights on small cap stocks, this could indicate that small cap stocks within the short leg of the *PDI* based strategy is responsible for most of the alpha generation.

4.3. *PDI*-Size relationship

4.3.1. Size and *PDI* sorted portfolios

We can analyze the size and *PDI* relationship more directly through double sorting our portfolios by both size and *PDI*. By double sorting our portfolios by *PDI* and size, we can discern the relationship between firm size and the performance of *PDI* based portfolios. In Table 5 we calculate annual alphas of the double-sorted portfolios against Fama-French-Carhart model.

In untabulated results, we have reversed the order of sorting, such that portfolios are first sorted into size quintiles, and then *PDI* deciles. The outcomes remain consistent with the analysis below, adding further credibility to our findings.

Table 5. Annual alphas of size and PDI sorted portfolios against Fama-French-Carhart model

The table reports annual alphas of double-sorted portfolios by size and PDI. Our observations are first sorted into PDI deciles, which are then sorted into quintiles based on size. Annual alphas are calculated against the Fama-French-Carhart model. Monthly alphas are annualized through multiplying by 12 (no compounding). "PDI Core" displays the average alpha for PDI deciles 2-9.

	***PDI* deciles**		
Size quintiles	*PDI* Bottom Decile	*PDI* Core (Deciles 2-9)	*PDI* Top Decile
Small	-37.2	-32.2	-9.7
2	-19.7	-32.7	-12.9
3	-14.6	-5.4	5.5
4	-11.5	-21.6	9.7
Big	-13.6	-5.0	3.3

As alpha estimates are subject to various factors, including data selection, model specification and market conditions, which may impact their magnitude, we complement our alpha estimates with a table of average annual returns for the double-sorted portfolios in Table 6. Average returns offer a simple overview of portfolio performance without reliance on specific model assumptions.

Table 6. Average annual return of size and PDI sorted portfolios

The table reports average annual returns of double-sorted portfolios by size and PDI. Our observations are first sorted into PDI deciles, which are then sorted into quintiles based on size. Average monthly returns are obtained through time series arithmetic averaging of each PDI-Size portfolio. Monthly average returns are then annualized through multiplying by 12 (no compounding).

	***PDI* deciles**		
Size quintiles	*PDI* Bottom Decile	*PDI* Core (Deciles 2-9)	*PDI* Top Decile
Small	-25.9	-19.7	-4.8
2	-11.8	-19.5	0.8
3	-11.1	5.8	12.8
4	-5.5	-4.9	17.7
Big	-2.4	4.3	11.4

Our findings indicate that the performance of *PDI* deciles varies between different firm sizes, for both alphas and average returns. Table 5 shows that annual alphas for the bottom decile ranges between -11.5% and -37.2%, of which the smallest quintile has the most negative alpha, and alphas for size quintiles 4 and 5 have less negative alphas of -11.5% and -13.6% respectively. This shows us why equal-weighted returns had a more pronounced alpha on the short leg in Table 4. At the same time, annual alphas for the top decile ranges between -12.9% and 9.7%, of which size quintiles 3-5 have alphas between 3.3%-9.7%, indicating that larger firms show more positive alphas for the top *PDI* decile. Looking at returns in Table 6, the smallest size quintile for the *PDI* bottom decile yields an average return of -25.9%, while the largest size quintile for the *PDI* top decile yields an average return of 11.4%.

We can interpret these results for the Size and PDI axes independently. For our sample, larger size seems to be uniformly correlated with higher returns, as the largest size quintiles has higher alpha and returns than the smallest size quintiles overall. Also, as expected, a higher *PDI* seems to predict higher alpha and returns across different size quintiles. The fact that alphas are skewed to the negative side might explain why we find that most of the alpha in the *PDI*-based portfolio originates from the short leg.

However, perhaps the most interesting question is whether the predictability of *PDI* is dependent on size. Seemingly, the differentials between the top and bottom *PDI* deciles for the smaller size quintiles are slightly higher in magnitude than the larger size quintiles, indicating that *PDI* might have more predictive power for smaller firms. We further test the dependability of *PDI* and size in a more direct and formal way through a regression with a *PDI-Size* interaction term in the next section.

4.3.2. Cross-sectional regressions with *PDI*-Size interaction term

Going back to cross-sectional regressions in a Fama-Macbeth setup, we can investigate the *PDI*-Size relationship through regressions with an interaction term. A *PDI*-Size interaction term allows us to investigate whether the relationship between *PDI* and returns changes dependent on firm size. We represent firm size using a dummy variable, providing coefficients that are readily interpretable. The size dummy takes a value of 1 for firms that exceed the median size and 0 otherwise, which splits the sample into two equally sized groups. The size dummy is also included independently in the regression equation, to capture the effect of size on returns on a stand-alone basis. In Table 7, we present results both including and excluding control variables. The regressions are computed with the following equations:

$$R_{t+1} = PDI + \; Size\ Dummy + (PDI * Size\ Dummy) \tag{1}$$

$$R_{t+1} = PDI + \; Size\ Dummy + (PDI * Size\ Dummy) + [Control\ Variables] \tag{2}$$

Table 7. Cross-sectional regressions with PDI-Size interaction terms

The table shows average slope coefficients and corresponding t-values (in parentheses) from cross-sectional regressions of next month returns against PDI, Size and the PDI-Size interaction term. We present results both including and excluding control variables.

	Regression:	
Variable	(1) Excl. Control Variables	(2) Incl. Control Variables
PDI	4.80***	3.80**
	(4.50)	(3.30)
Size Dummy	2.20***	1.70**
	(3.40)	(2.40)
*PDI * Size Dummy*	-2.70**	-2.30*
	(-2.20)	(-1.70)

Note: *p<0.1; **p<0.05; ***p<0.01

The stand-alone coefficient of the size dummy represents the difference in the intercept between large firms and small firms. For the regression without control variables, we find that the size dummy is highly significant at a t-value of 3.40, which indicates that size is positively correlated with stock returns. The regression including control variables also shows a significantly positive coefficient for the size dummy at a t-value of 2.40. When interpreting this coefficient in financial terms, this implies that firms with above median market cap on average yield 1.7 – 2.2% higher returns in the next month, when *PDI* is 0.

More importantly, the *PDI-Size* interaction term is significant at a t-value of -2.20 for the regression excluding control variables, and weakly significant at a t-value of -1.70 for the regression including control variables. Therefore, our results indicate the presence of a negative interaction between *PDI* and Size. A negative interaction term indicates that when the firm size is smaller, the combined coefficient of *PDI* becomes larger. In other words, we find evidence that firm size is negatively correlated with the return predictability of *PDI*. This is in line with our findings that alphas are larger for our equal-weighted portfolios, which contain a higher weighting on small-cap stocks. In financial terms, this means that *PDI* has a coefficient of 4.8% for small firms, but 2.1% (4.8%-2.7%) for large firms. This shows that the effect of firm size on PDI also has economically significant implications.

5. Discussion

In this section we present our key findings and discuss their implications.

5.1. Significance and persistence of PDI in explaining future stock returns

From our cross-sectional regressions of *PDI* against raw returns, Fama-French-Carhart adjusted returns, and market adjusted returns, we find that *PDI* has high predictability in the short-term, with highly significant coefficients against next month returns in all three cases, as well as moderately significant coefficients for returns in months 2-6 and in most cases for months 7-12 months too (with *PDI* being weakly significant against Fama-French adjusted returns). For even longer time horizons, such as for months 13-24 we see that the predictability disappears, with none of the coefficients for that time horizon being significant (not even for unadjusted returns). We see a similar pattern for alphas of *PDI*-based zero-cost portfolios, where the magnitude of alphas declines for longer time horizons.

This finding slightly differs between our study and Avramov et al. (2020) who find that *PDI* has high significance even for months 13-24. Overall, Avramov et al. (2020) also have markedly higher coefficients and t-values across all time horizons compared to our study.

The fact that we find that the return predictability of *PDI* deciles for longer time horizons aligns with the notion that new financial information is fully incorporated into the stock price after a stock price adjustment interval (i.e. drift). Following new quarterly financials, investors might underreact to new financial information, which causes a delayed price adjustment. However, in due time, the new information will be incorporated into the stock price. This mechanism could be similar to the Post-Earnings Announcement Drift (PEAD) phenomenon where a stock's price continues to drift in the direction of an earnings surprise due to delayed information processing, behavioral biases, or information asymmetry.

Although we find that the significance of *PDI* is slightly lower and less persistent than that of Avramov et al. (2020), the results still indicate that *PDI* is a strong predictor of future returns, which could potentially be utilized to generate alpha in the Swedish stock market through a long-short strategy based on *PDI* sorted portfolios, such as done in this study. As *PDI* has higher return predictability for shorter time horizons, a portfolio that is rebalanced more frequently would yield higher returns.

5.2. Long and short leg performance

We find that the performance of *PDI* is mostly attributable to the short leg of the long-short strategy, implying that firms with negative deviations from previous average fundamentals show negative stock returns. In contrast, Avramov et al. (2020) found that most of the performance of *PDI* can be derived from the long leg.

Our conclusion is in line with Stambaugh, Yu and Yuan (2012), who show that most anomalies largely derive their profitability from the short leg. Stambaugh, Yu and Yuan (2012) argue that overpricing should be more prevalent than underpricing due to short-sale impediments, and that the profitability of anomalies are consistent with this setting.

Because the profitability of *PDI* largely stems from the short leg of the zero-cost portfolio, the real-world applicability and exploitability of *PDI* could be hindered by short-sale constraints. Short-sale constraints encompass a variety of regulations and limitations imposed on investors who wish to engage in short selling activities. These constraints include margin restrictions, limited availability of short sellable stocks, and reporting requirements. Furthermore, D'Avolio (2002) find that the main suppliers of stock loans are institutional investors, and that the degree of institutional ownership explains much of the variation in loan supply across stocks, such that stocks with low institutional ownership are more expensive to borrow. Apart from transaction costs, holding costs can also make short-selling costly due to idiosyncratic risk. Pontiff (2006) demonstrates that idiosyncratic risk during the holding period is the largest cost faced by arbitrageurs. Therefore, an avenue for future research on the practical implementation of the *PDI*-based strategy could be obtaining proxies for short-sell constraints or limits to arbitrage to further study the feasibility of the *PDI*-based strategy in real-world market conditions.

5.3. *PDI*-Size relationship

An aspect unexplored by Avramov et al. (2020) is the relationship between *PDI* and firm size. Therefore, a major contribution of our thesis is the investigation of the *PDI*-Size relationship.

Our results from both double sorted portfolios and regressions with a *PDI*-Size interaction term, indicate that there is a negative relationship between firm size and the return predictability of *PDI*. This implies that *PDI* has higher performance for small cap firms, which was also noticeable from the difference in performance between equal-weighted and value-weighted portfolios. This finding can be understood through several plausible explanations:

- <u>*Information efficiency*</u>: Larger-cap firms tend to have greater analyst coverage, more widely available information, and a higher degree of market efficiency. As a result, any deviations from past fundamentals might be more quickly incorporated into stock prices. In contrast, smaller-cap firms may receive less attention from analysts and investors, leading to slower incorporation of new information and greater potential for *PDI* to identify mispricing.

- *Sensitivity to new information:* Larger-cap firms often have more established business models, stable earnings streams, and stronger market positions, making them less sensitive to short-term fluctuations in fundamentals. Consequently, the market's reaction to new information or deviations from past fundamentals may be more muted for larger-cap firms, limiting the effectiveness of PDI in forecasting their future returns.
- *Liquidity:* Smaller-cap stocks often have lower trading volumes and higher bid-ask spreads, making them more susceptible to inefficiencies and price discrepancies. However, these discrepancies might not be fully exploitable due to the limited liquidity.

The fact that the return predictability of *PDI* is highest for small-cap firms further deteriorates the exploitability of *PDI* as a return predictor, because investors will incur higher transaction costs for wider bid-ask spreads and lower liquidity.

6. Conclusion

In this thesis, we draw inspiration from Avramov et al. (2020), and explore the significance of deviations between current values and moving averages of fundamentals (*PDI*) in predicting equity returns, with the hypothesis that investors are anchored to the long-term average and underreact to new financial information. We find support for this hypothesis as the return predictability of *PDI* is high for short-term time horizons, with significant coefficients in cross-sectional regressions against unadjusted returns as well as returns adjusted against Fama-French-Carhart factors while also including a selection of control variables.

Compared to Avramov et al. (2020), we find that the persistence of *PDI* is slightly lower, with non-significant coefficients for stock returns 13-24 months after the deviation measure. In addition, we have identified that the performance of *PDI* is primarily driven by the short leg of the long-short strategy, contrary to the findings of Avramov et al. (2020), who attributed most of the performance to the long leg.

We extend the analyses performed by Avramov et al. (2020) by further investigating the relationship between *PDI* and firm size, and reveal a negative relationship between firm size and the return predictability of *PDI*. This implies that *PDI* exhibits higher performance for small-cap firms, which we propose could be attributed to factors such as information efficiency, sensitivity to new information, and liquidity. The heightened return predictability of *PDI* for small-cap firms may pose challenges in terms of transaction costs and liquidity constraints for investors.

In conclusion, our study contributes to a deeper understanding of the significance and limitations of PDI as a return predictor, as well as its interaction with firm size. While *PDI* shows promise as a tool for generating alpha in the Swedish stock market, investors should be mindful of its performance characteristics and the challenges associated with its implementation, particularly in relation to short-sale constraints and firm size dynamics. Moving forward, further research into the practical implications and refinements of PDI-based investment strategies may offer valuable insights for investors and practitioners alike.

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Appendix A. Variable definitions

Cash and Short-term Investments (IQ_CASH_EQUIV) = reported cash and cash equivalents.

*Retained Earnings (*IQ_RE) = reported retained earnings, including profit/loss for the period.

Operating Income (IQ_EBIT) = reported earnings before interest items and tax.

Sales (IQ_TOTAL_REV) = reported total revenue.

Capital Expenditures (IQ_CAPEX) = reported gross investments in long-term assets impacting cash flow statement.

Invested Capital (IQ_TOTAL_CAP) = reported total common equity (including minority interest) plus total debt.

Inventories (IQ_INVENTORY) = reported value of inventory.

Book-to-market (IQ_PBV) = stock price divided by reported total common equity (including minority interest) per share.

Return on Assets (IQ_ROA) = reported earnings before interest items and tax divided by average total assets.

Return on Equity (IQ_RETURN_EQUITY) = net income divided by total average common equity (including minority interest).

Daily Volume (IQ_VOLUME) = total monthly shares traded.

Shares Outstanding (IQ_CLASS_SHARESOUTSTANDING) = the total number of shares outstanding at end of month.

Turnover (IQ_VOLUME / IQ_CLASS_SHARESOUTSTANDING) = total monthly shares traded divided by the total number of shares outstanding at end of month.

Appendix B1. Cross-sectional regressions of raw returns against *PDI*

This table reports average slope coefficients and corresponding t-values (in parentheses) from monthly cross-sectional regressions of raw returns over (i) next month, (ii) months 2-6, (iii) months 7-12, (iv) months 13-24 against PDI and the control variables defined in section 3.4. We also report the average R^2 of the monthly cross-sectional regressions. In Panel B, we also show the results for regressions without control variables. Note that the dependent variables (returns) are computed in percentage points, while predictors are computed in decimal form. Coefficients are interpreted as the percentage points change in returns from one unit change in the predictor.

Panel A: Full regressions:

	Dependent variable:			
	R_{t+1}	$R_{t+2:t+6}$	$R_{t+7:t+12}$	$R_{t+13:t+24}$
PDI	2.90***	4.70***	4.00**	0.32
	(3.50)	(3.20)	(2.10)	(0.09)
Log Size (*ME*)	0.05	-0.24**	-0.47***	-1.40***
	(0.83)	(-2.00)	(-3.20)	(-5.20)
Book-to-Market (*BE/ME*)	-0.20	-0.52	-0.25	-0.71
	(-0.93)	(-1.20)	(-0.52)	(-0.85)
Return over months -12 to -2 (*MOM*)	1.40***	2.40***	1.30**	1.90*
	(4.50)	(5.00)	(2.20)	(1.90)
Return on Assets (*ROA*)	-0.22	3.30	-13.00***	-17.00***
	(-0.12)	(1.10)	(-3.40)	(-2.60)
Return on Equity (*ROE*)	0.69	-0.08	4.50***	6.80***
	(1.40)	(-0.08)	(4.00)	(3.10)
Turnover (*TURN*)	2.70	0.40	1.40	12.00
	(1.50)	(0.09)	(0.31)	(1.10)
Averaged R^2	0.25	0.27	0.26	0.30

Note: *p<0.1; **p<0.05; ***p<0.01

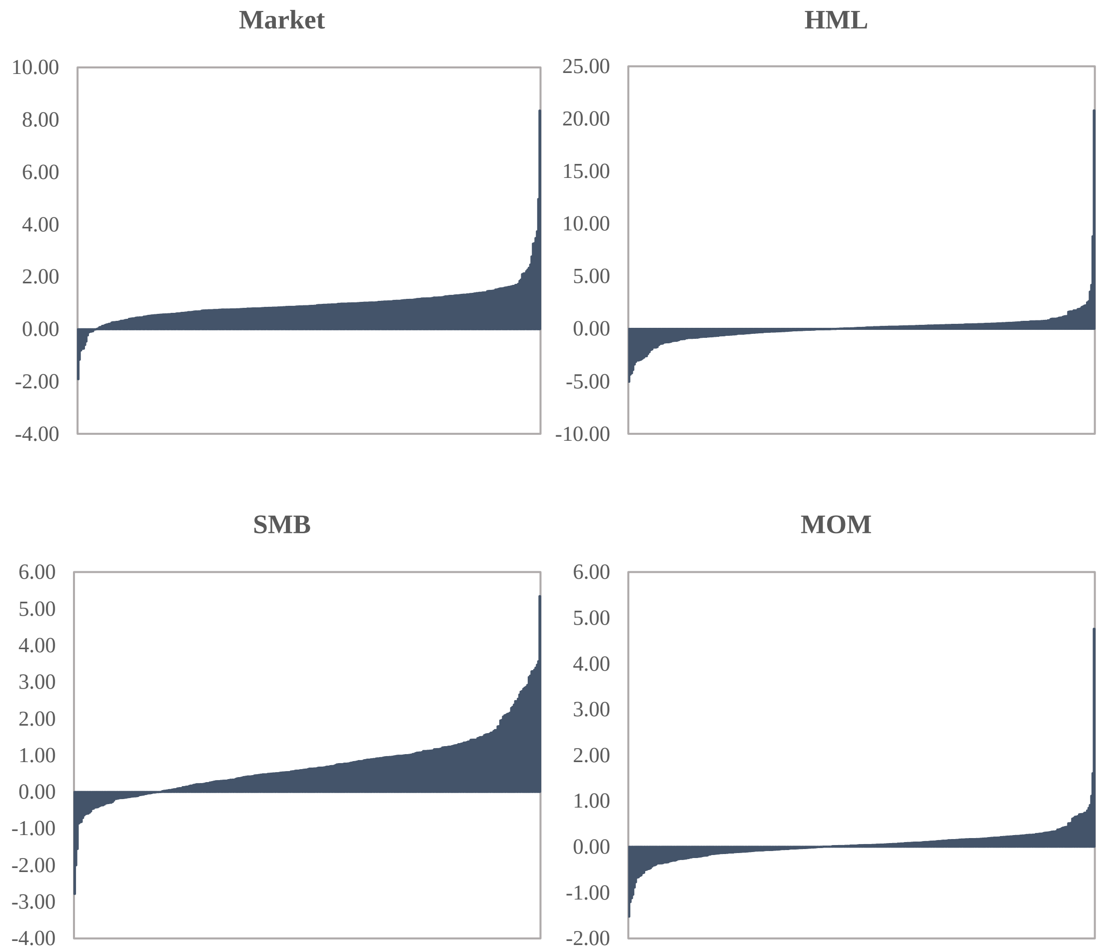
Panel B: Regressions without control variables:

	Dependent variable:			
	R_{t+1}	$R_{t+2:t+6}$	$R_{t+7:t+12}$	$R_{t+13:t+24}$
PDI	4.10***	6.60***	4.60***	-2.30
	(5.30)	(4.90)	(2.60)	(-0.60)

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix B2. Fama-French-Carhart factor loadings distributions

The plots show the distribution of factor loadings for the Fama-French-Carhart factors for all 393 firms in our sample. The firms, along the x-axis, are sorted in ascending order based on each factor. The y-axis represents factor loadings. The factor loadings are obtained through separate time series regressions of returns against Fama-French-Carhart factors for each firm.



Appendix B3. Cross-sectional regressions of Fama-French-Carhart adjusted returns against *PDI*

This table reports average slope coefficients and corresponding t-values (in parentheses) from monthly cross sectional regressions of Fama-French-Carhart adjusted returns over (i) next month, (ii) months 2-6, (iii) months 7-12, (iv) months 13-24 against PDI and the control variables defined in section 3.4. We also report the average R^2 of the monthly cross-sectional regressions. Dependent variables (returns) are computed in %, while predictors are computed in decimal form. So, coefficients are interpreted as the percentage points change in returns from one unit change in the predictor.

	Dependent variable:			
	Adj. R_{t+1}	***Adj.*** $R_{t+2:t+6}$	***Adj.*** $R_{t+7:t+12}$	***Adj.*** $R_{t+13:t+24}$
PDI	3.60^{***}	5.10^{**}	4.40^{*}	-2.10
	(3.90)	(2.50)	(1.70)	(-0.54)
Log Size (*ME*)	0.16^{***}	0.74^{***}	0.87^{***}	1.30^{***}
	(2.60)	(5.10)	(4.70)	(5.00)
Book-to-Market (*BE/ME*)	-0.22	-1.50^{**}	-0.83	-1.60
	(-0.97)	(-2.50)	(-1.30)	(-1.40)
Return over months -12 to -2 (*MOM*)	2.20^{***}	7.10^{***}	7.10^{***}	10.00^{***}
	(6.20)	(11.00)	(10.00)	(7.50)
Return on Assets (*ROA*)	-1.20	-1.40	-24.00^{***}	-29.00^{***}
	(-0.63)	(-0.37)	(-4.30)	(-4.30)
Return on Equity (*ROE*)	0.54	-0.70	3.50^{**}	4.90^{**}
	(0.90)	(-0.53)	(2.20)	(2.20)
Turnover (*TURN*)	5.00^{**}	16.00^{***}	19.00^{***}	32.00^{***}
	(2.50)	(2.80)	(3.00)	(3.40)
Averaged R^2	0.11	0.12	0.11	0.13

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix B4. Cross-sectional regressions of market adjusted returns against *PDI*

This table reports average slope coefficients and corresponding t-values (in parentheses) from monthly cross-sectional regressions of market adjusted returns (R_i – R_m). *over (i) next month, (ii) months 2-6, (iii) months 7-12, (iv) months 13-24 against PDI and the control variables defined in section 3.4. We also report the average* R^2 *of the monthly cross-sectional regressions. Dependent variables (returns) are computed in %, while predictors are computed in decimal form. So, coefficients are interpreted as the percentage points change in returns from one unit change in the predictor.*

	Dependent variable:			
	$(R_i - R_m)_{t+1}$	$(R_i - R_m)_{t+2:t+6}$	$(R_i - R_m)_{t+7:t+12}$	$(R_i - R_m)_{t+13:t+24}$
PDI	3.50***	6.20**	7.20**	-4.00
	(3.20)	(2.50)	(2.50)	(-1.00)
Log Size (*ME*)	0.18**	0.75***	0.73***	1.20***
	(2.20)	(3.90)	(3.10)	(3.60)
Book-to-Market (*BE/ME*)	-0.24	-1.40*	-0.72	-1.00
	(-0.85)	(-1.90)	(-1.00)	(-1.00)
Return over months -12 to -2 (*MOM*)	2.40***	6.90***	5.90***	7.80***
	(5.50)	(7.50)	(7.30)	(6.50)
Return on Assets (*ROA*)	-0.90	-0.71	-26.00***	-30.00***
	(-0.39)	(-0.15)	(-4.70)	(-4.10)
Return on Equity (*ROE*)	0.70	0.31	5.30***	8.10***
	(1.00)	(0.20)	(3.40)	(3.50)
Turnover (*TURN*)	5.60**	16.00**	24.00***	38.00***
	(2.40)	(2.50)	(3.40)	(3.50)
Averaged R^2	0.14	0.15	0.14	0.18

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix C1. Annual alphas of size and PDI sorted portfolios against Fama-French-Carhart model (Table 7 - Full-sized)

The table reports annual alphas of double-sorted portfolios by PDI and size. Our observations are first sorted into PDI deciles, which are then sorted into quintiles based on size. Annual alphas are calculated against the Fama-French-Carhart model. Monthly alphas are annualized through multiplying by 12 (no compounding).

	PDI **deciles**									
Size quintiles	*Bottom*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*Top*
Small	-37.2	-33.2	-47.3	-17.7	-51.9	-37.5	-39.4	-11.7	-18.7	-9.7
2	-19.7	-38.6	-45.2	-27.4	-38.8	-33.5	-34.3	-27.3	-16.6	-12.9
3	-14.6	-10.0	-2.8	-4.4	-19.8	3.1	-10.4	-3.9	5.1	5.5
4	-11.5	-29.2	-20.9	-17.4	-18.5	-34.7	-16.3	-5.8	-29.6	9.7
Big	-13.6	-1.5	0.3	0.0	-5.8	-14.8	-0.3	-4.8	-13.1	3.3

Appendix C2. Average annual return of size and PDI sorted portfolios (Table 8 – Full-sized)

The table reports average annual returns of double-sorted portfolios by size and PDI. Our observations are first sorted into PDI deciles, which are then sorted into quintiles based on size. Average monthly returns are obtained through time series arithmetic averaging of each PDI-Size portfolio. Monthly average returns are then annualized through multiplying by 12 (no compounding).

	PDI **deciles**									
Size quintiles	*Bottom*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*Top*
Small	-25.9	-31.8	-31.4	-7.9	-27.0	-23.6	-21.6	-13.8	-0.6	-4.8
2	-11.8	-27.1	-31.7	-13.2	-30.4	-22.1	-14.9	-13.2	-3.0	0.8
3	-11.1	-1.5	8.5	10.0	-6.0	9.9	3.9	6.8	14.5	12.8
4	-5.5	-17.3	-7.5	-4.7	-6.3	-12.6	0.3	8.7	0.0	17.7
Big	-2.4	4.8	6.7	7.8	6.8	-1.1	5.1	6.3	-1.8	11.4