Thesis

MSc Finance

Q-factor Investment Approach: Evidence from the Swedish Equity Market

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Abstract

Four easily measured factors: market, size, investment, and profitability together constitute the empirical q-factor model. The combination of factors have previously shown to largely capture the cross-sectional variation in average stock returns. An extensive examination of data from the Swedish equity market concludes that the q-factor model is not applicable. Additional tests demonstrate modest findings in line with previous literature. The study does provide evidence of a positive profitability-expected return relation.

Keywords: *Asset pricing, q-factor model, Swedish equity market*
JEL Classification: G12, G14

1 Introduction

In our study, we create a q-factor model in an attempt to investigate the validity of such model on the Swedish equity market from July 2010 to June 2020. Our thesis is predominately inspired by Hou et al. (2015) in terms of model construction and factor definitions. Moreover, as for Hou et al. (2015), the base of our created q-factor model stems from the investment-based asset pricing model and the neoclassical q-theory [1] of investment. Our ambition throughout the thesis has been to certify the validity of the q-factor model by implementing it on a new market (the Swedish equity market) and over a modern time period in the 21st century. To our knowledge, the q-factor model have not been tested under aforementioned conditions. The basis behind the q-factor model is to successfully be able to summarize the cross-section of average stock returns. The constructed q-factor model contains four factors: market, size, investment, and profitability. The Swedish market factor (MKT_t) is defined by the SIX return index. The size factor ($\mathrm{r}_{MC,t}$), dependent on market capitalization, is defined as the difference between the return on a portfolio of small and big size stocks. The investment factor ($\mathrm{r}_{I/A,t}$), measured through the investment-to-asset ratio (I/A), is defined as the difference between the return of a low investment stock portfolio versus a high investment stock portfolio. Vice versa, the profitability factor ($\mathrm{r}_{Roe,t}$), measured based on the return-on-equity (ROE), is defined as the difference between the return

[1] The q-theory is closely aligned to the neoclassical theory of investment, stating that increased investment follows when marginal product of capital is greater than cost of capital (Kaldor, 1966).

of a high profitability stock portfolio versus a low profitability stock portfolio. The tested q-factor model,

$$\mathrm{R}_t^i - \mathrm{r}_t^f = \alpha^i + \beta_{MKT}^i \mathrm{MKT}_t + \beta_{MC}^i \mathrm{r}_{MC,t} + \beta_{I/A}^i \mathrm{r}_{I/A,t} + \beta_{Roe}^i \mathrm{r}_{Roe,t} + \epsilon^i \tag{1}$$

in which MKT, r_{MC}, $\mathrm{r}_{I/A}$, and r_{Roe} are the factor premiums while β_{MKT}^i, β_{MC}^i, $\beta_{I/A}^i$, and β_{Roe}^i are the factor loading's as expressed in Hou et al. (2015).

Our constructed q-factor model is based on a triple two-by-three-by-three [2] sorting on size, investment, and profitability – henceforth called the interaction portfolios. Ahead of evaluating the q-factor model, we create additionally 40 portfolios based individually on size, investment, profitability, and book-to-market. The results of the individually created portfolios shows that only the profitability factor is significantly different from zero at the 5% level (0.77%, t = 2.4684). Similar results are obtained from the interaction portfolios where the size factor earns an average return of 0.20% (t = 0.7373), the investment factors earns an average return of 0.21% (t = 0.8377), and the profitability factor earns an average return of 1.40% (t = 4.9559). In essence our findings are scarce and do not strengthen the validity of the q-factor model in a changing setting in terms of geography and sample period. The contribution of this paper is still meaningful as it adds to additional knowledge of the q-factor model, but also as our research indicates some characteristics in line with previous research in other markets. E.g., the ambiguous findings of a market capitalization-expected return relation, a modest degree of negative investment-return relation, and a significant positive profitability-expected return relation.

Altogether our findings are undeniably trivial and no profound interpretations or implications of our results should be derived. We made additional analysis, such as changing the time setting and how the weights of the portfolios are constructed, but neither when doing this were we able to give any additional information regarding the validity of the model. Perhaps, since the q-factor model is in reduced form, the model is unable to fully grasp co-movements between factors, which in part could explain the insignificant results of this study. In addition to previous research made on the subject, our focus on the Swedish market gives a wider perspective and further understanding regarding the performance of the q-factor model in various settings. Not the least on the Swedish market but also in a modern economy and on a smaller scale compared to e.g., the US market tested in Hou et

[2] Triple sorting where the size factor (r_{MC}) is split into two groups based on the median, the investment factor ($\mathrm{r}_{I/A}$) is split into three groups based on the ranked values of I/A, and the profitability factor (r_{Roe}) is split into three groups based on the ranked values of ROE.

al. (2015). Ultimately, this thesis serves as an addition to our understanding of the q-theory of investment and with a focus on the unexplored Swedish equity market. Moreover, our examination in a changing setting adds to foregoing research on the subject, but in isolation addresses the question; *Is the q-factor model applicable on the Swedish equity market and to what extent?*

1.1 Thesis structure

The paper is structured as follows, section two provides a review of the literature on the q-factor model together with explanations of thesis hypotheses. Section three presents the methodology of our study with detailed descriptions of our approach throughout the entire research. Section four presents our empirical results together with a comprehensive discussion regarding our findings and additional sensitivity analyses. In section five we conclude our findings.

2 Literature

Many of the fundamental and most prominent studies made on past performance as a proxy for future performance explain the movements on the financial markets through the use of theories such as the random walk hypothesis, efficient market hypothesis, or other cross-sectional analyses. The literature is vast and in this section we pursuit to pinpoint the most valuable and important papers that impacted our understanding and writing of this thesis.

Sprung from the capital asset pricing model (CAPM) (see Sharpe, 1964; Lintner, 1965; Black, 1972), Fama and French (1993) identified three common risk factors in the return of stocks: a market factor, a size factor, and a book-to-market equity factor. Fama and French (1993) were able to summarize the cross-section of average stock returns on the US market for the perid 1963-1990. The size effect is heavily explored in financial literature with Banz (1981) as one of the most pronounced studies. Banz (1981) examined the relationship between return and the total market value of NYSE common stocks, and found that smaller firms have had – on average – higher risk adjusted returns than larger firms. Thereafter, several studies have tested and found a size effect both in the US (e.g., Reinganum, 1981; Keim, 1983; Lamoureux and Sanger, 1989) and internationally (e.g., Beedles, 1992; Bagella et al., 2000; Elfakhani et al., 1998). More recent papers suggest that the size effect disappears post early 1980s (e.g., Eleswarapu and Reinganum, 1993; Dichev, 1998, Amihud, 2002), and

Dimson and Marsh (1999) show that the size premium actually reversed in the UK. Hirshleifer (2001) suggests that the size anomaly disappears around time of discovery which is similar to the findings in Hou et al. (2018) where 82% of the anomalies tested failed to uphold acceptable standards and where even replicated anomalies had smaller economic magnitude than originally reported. However, Van Dijk (2011) states that, "the conclusion that the size effect has gone away is premature"(p.3272) meaning that there has been a size premium in recent years. Van Dijk (2011) believes that more empirical research is needed to examine the robustness of the size effect on US and international equity markets. The other factor in Fama-French three factor model, book-to-market, is also proven to be extensively researched in academia and found to be positively correlated with average returns on US stocks (e.g., Stattman, 1980; Rosenberg et al., 1985). The book-to-market factor further proved to have a significant role in explaining the cross-section of average returns on Japanese stocks (Chan et al., 1991).

In the end of the 20th century the Fama-French three-factor model failed to account for many asset pricing anomalies (see e.g., Daniel and Titman, 2006; Cooper et al., 2008; Campbell et al., 2008). With that in mind, Hou et al. (2015) created a new empirical model that also summarizes the cross-section of average stock returns while avoiding several anomalies faced in Fama and French (1993). Their model is inspired by the q-theory of investment by using a triple two-by-three-by-three sorting on size, investment, and profitability. Hou et al. (2015) proposed q-factor model is similar to that of Fama and French (2015), but the sorting variables for investment and profitability are defined differently. Profitability is used as a factor and illustrates a positive relationship where high expected profitability firms earn higher expected returns than lower profitability firms and vice versa for low expected profitability firms. Novy-Marx (2013) found that profitable firms – despite having higher valuation ratios – generate significantly higher returns than unprofitable ones. This relation is also consistent with the standard discount model in which, with some derivation, the expected return equals the expected profitability divided by the market-to-book ratio. By multiplying the numerator and denominator with the book equity it would equal the expected return with the ratio of the expected cash flows over the market equity. Another important implication, according to Hou et al. (2015), is that of momentum winners having higher expected returns than momentum losers. This leads to firms where positive shocks to profitability are positively correlated with stock returns, to experience immediate stock price increases, where vice versa holds true. Hou et al. (2015) also discuss how "[...] less financially distressed firms are more profitable, meaning higher expected profitability, and, all else equal, should earn higher expected returns [...](p.658). Hou et al. (2015) show the intuition behind using investment as a factor in the q-factor model by using a two-period stochastic general equilibrium model, where high investment stocks should earn lower expected return than low investment stocks. In the end, Hou et al. (2015) findings suggest that the q-factor model outperforms the three-factor model and four-factor model of Fama and French (1993) and Carhart (1997) respectively in capturing anomalies such as momentum on the US market. In essence, Hou et al. (2015) findings are critical as a q-factor model that capture momentum through the profitability factor advocates information contained in past stock prices regarding expected profitability and/or expected growth.

Aforementioned results are further substantiated by the findings in George et al. (2016), who also find clear evidence of the q-factor model outperforming other factor models, specifically in capturing the price-to-high (PTH) anomaly. George et. al. (2016) reveals a positive relation between PTH and expected profitability as well as between PTH and expected investment growth. The findings are in line with the CAPM, where stocks with higher expected profitability and investment growth will have higher expected returns. Similarly to Hou et al. (2015), George et al. (2016) findings suggests that the q-factor model surpass the other factor model in capturing extreme returns. Asad and Cheema (2017) is another paper which further complements the findings of Hou et al. (2015). Asad and Cheema (2017) investigate the validity of the q-factor model by assigning the model to the Karachi Stock Exchange (Pakistan), testing the legitimacy of the model in an emerging market setting. The findings are in accordance with previous literature and that the q-factor model has better explanatory power than the traditional CAPM model, thus further increasing the validity of the q-factor model. Asad and Cheema (2017) demonstrate how investment can be used as a tool for fundamental analysis since as firms increase their investment, their stock returns decline.

2.1 Factor intensity

As presented, previous literature on the subject is plentiful; however, they differ in magnitude, geographical settings, as well as explanatory power. Analogically to Hou et al. (2015), our study aims to implement the q-factor model, however, on the so far untested (to our knowledge) Swedish equity market. The q-factor model is formed based on four factors: market, size, investment, and profitability. A recorded trend among previous literature suggests that the size factor have a significant effect on return. Previous studies such as Banz (1981) calls for a notable size effect, where smaller firms generally have higher risk adjusted returns than larger firms. Ever since, other studies have proved the opposite, with contrary results to that of Banz (1981). Unanimous findings by studies such as Amihud, (2002), Dichev (1998), Dimson and Marsh (1999), and Eleswarapu and Reinganum (1993) sugests the contrary. In addition, Hou et al. (2015) mentions that the size factor had a limited role in their constructed q-factor model. The extensive literature review presented together with above discussion renders our first hypothesis:

Hypothesis 1: Portfolios of small firms earns higher returns on average than portfolios of large firms.

The topic of investment and its effect on expected return is well documented and mostly straightforward. As expressed in Hou et al. (2015), "Firms invest more when their marginal q (the net present value of future cash flows generated from an additional unit of assets) is high. Given expected profitability or cash flows, low discount rates imply high marginal q and high investment, and high discount rates imply low marginal q and low investment." (p.655). All else equal, high investment stocks should earn lower expected return than low investment stocks, and vice versa being true, which is in accordance with our second hypothesis:

Hypothesis 2: Portfolios of low-investment firms earns higher returns on average than portfolios of high-investment firms.

The last piece of the q-factor model is that of the profitability factor. Research suggest that firms with high expected profitability, should earn higher expected return (see e.g., Hou et al., 2015 and Novy-Marx, 2013). Such positive profitability-expected return relation obey the standard discount model in which expected return equals the expected profitability over market-to-book ratio. Moreover, another widespread phenomena is that of momentum also being a positive driver of return. Arguments raised in Hou et al. (2015), suggests that momentum winners should have higher expected return than momentum losers. E.g., firms where positive shocks to profitability are positively correlated with stock return, in which they will experience immediate stock price increases. In addition to present discussion, Hou et al. (2015) expand on theories regarding financial distressed companies. The relationship between financial distressed companies and profitability is well documented where less financially distressed companies on average are more profitable and as such earn higher expected returns. The findings and evidence in Hou et al. (2015) is in complete line with our third hypothesis:

Hypothesis 3: Portfolios of high-profitability firms earns higher returns on average than portfolios of low-profitability firms.

As displayed, Hou et al. (2015) findings and arguments are in direct support of our constructed hypotheses. Besides the relationship discussed about firm size effect on expected return, both profitability and investment are conditional on each other (e.g., profitable firms are more inclined to invest more than less profitable firms). In essence, *hypothesis 2* and *hypothesis 3* depend on each other and moderate conclusion should be drawn for each hypothesis individually.

3 Methodology

The q-factor model is comprised of the four factors: market, size, investment, and profitability. The SIX RX works as a proxy for the return of the Swedish equity market, market capitalization (MC) for size, investment-to-asset ratio (I/A) for investment, and return on equity (ROE) for profitability.

3.1 Data source and sample

Acquired from the *Bloomberg terminal*, the population consists of all companies listed on Nasdaq Stockholm main list during the period 2010-2020. Likewise, downloaded from *Compustat Global* and *Compustat North America* are the corresponding data for these companies. All preferential shares are excluded. Table 1 presents the number of companies for each year, where the total amount of Bloomberg Tickers represents the population while the total amount of Compustat represents our sample. In addition, table 1 displays a summary of the missing variables for each factor throughout the sample period. The number of companies in the sample showed minor variations in the first half of the sample period (low-point of 244 companies in 2012 and 2013) but then increased substantially from 2014 and onwards (high-point of 318 companies in 2019).

3.2 Factor calculations

Downloaded from *Compustat Global - Security daily* are the price close daily (PRCCD), the daily return factor (TRFD), shares outstanding (CSHOC), and adjustment factor (AJEXI) for each share. The daily return factor includes cash equivalent distribution along with reinvestment of dividends while the adjustment factor makes sure that the return of the company takes share splits and/or new share issues into consideration. Similarly, we attained all accounting information, denoted in different currencies, from *Compustat - Fundamentals*

Date	**Bloomberg Tickers**	**Compustat**	**Missing Values**			
			Size	I/A	ROE	BM
2010-06	287	249	3	3	9	11
2011-06	287	251	3	1	7	8
2012-06	276	244	3	1	5	5
2013-06	280	244	3	1	5	5
2014-06	282	246	5	0	9	7
2015-06	298	262	0	1	10	13
2016-06	309	274	0	1	6	6
2017-06	331	294	2	1	11	10
2018-06	349	308	0	1	15	12
2019-06	364	318	2	2	11	19

Note: Bloomberg ticker is the total number of companies – referred to as the population – while Compustat is the total amount of companies in the data set and referred to as the sample.

Table 1: Data sample for each year

Annual and *Compustat - Fundamentals Quarterly*. We downloaded both SIX RX and the three-month STIBOR – used as the risk-free rate – from the *Bloomberg terminal* together with exchange rates (FX). All calculations in equation 2 through 11 is based on the structure in Hou et al. (2015). Ahead of extracting the returns, we adjusted the share price and denoted all sampled companies in SEK:

$$\text{PRCFX}_t^i = \text{PRCCD}_t^i \times FX_t^i \tag{2}$$

Next, we adjusted the stock prices to take dividends, share splits and/or new share issues into consideration:

$$\text{Adj. Stock price}_t^i = \frac{\text{PRCFX}_t^i}{\text{AJEXI}_t^i \times \text{TRFD}_t^i} \tag{3}$$

Thereafter the adjusted stock prices were used to calculate the monthly returns:

$$\text{Return}_t^i = \frac{\text{Adj. Stock price}^i}{\text{Adj. Stock price}_{t-1}^i} - 1 \tag{4}$$

The market capitalization calculated as:

$$\text{MC}_t^i = \text{PRCFX}_t^i \times \text{CSHOC}_t^i \tag{5}$$

Our population contains companies that have multiple share classes listed; however, we only allow for one share class per company. Hence, the sum of the market capitalization for these share classes is used throughout the study.

$$\mathrm{MC}_t^{i+j} = \mathrm{MC}_t^i + \mathrm{MC}_t^j \tag{6}$$

As such, we extract the returns for these companies as the sum of the market weighted return for each share class:

$$\mathrm{Return}_t^{i+j} = \mathrm{Return}_t^i \times \frac{\mathrm{MC}_t^i}{\mathrm{MC}_t^{i+j}} + \mathrm{Return}_t^j \times \frac{\mathrm{MC}_t^j}{\mathrm{MC}_t^{i+j}} \tag{7}$$

We measure investment-to-asset, as the annual change in total asset (Compustat annual item AT), thus total asset divided by the one year lagged total asset. The investment-to-asset ratio is sorted at the end of June each year with data from the fiscal year ending in calendar year $t-1$:

$$\mathrm{I/A\ ratio}_t^i = \frac{\mathrm{Total\ Asset}_t^i}{\mathrm{Total\ Asset}_{t-1}^i} \tag{8}$$

We measure profitability as the income before extraordinary items (Compustat quarterly item IBQ) divided with one quarter lagged book common equity (BE) [3]. We use the data downloaded from Compustat quarterly files for those months immediately following the most recent public quarterly report. For example, if earnings for the first fiscal quarter of year t are publicly announced in June, we use that announced net income (divided by the book common equity from the fourth quarter of year $t-1$) to form portfolios in July:

$$\mathrm{ROE}_t^i = \frac{\mathrm{Net\ Income}_t^i}{\mathrm{Book\ Common\ Equity}_{t-1}^i} \tag{9}$$

We extract the book-to-market (BM) to be able to compare the q-factor model with the Fama-French three-factor model (Fama and French, 1993). We define BM as the book

[3] Stockholders' equity, quarterly item SEQQ in Compustat.

common equity divided by the market capitalization for month$_{t-1}$:

$$\text{Book-to-Market}_t^i = \frac{\text{Book Common Equity}_t^i}{\text{Market Cap}_{t-1}^i} \tag{10}$$

We convert the risk-free rate into monthly returns using:

$$\text{Monthly Return} = (1 + \text{annual return})^{\frac{1}{12}} \tag{11}$$

3.3 Value-weighted portfolio returns

As in both Hou et al. (2015) and Asad and Cheema (2017), the weight allocated to each share in the portfolio for month t is determined by their MC month $t-1$ in relation to the total portfolio weight. The weighted allocation cause larger companies in a portfolio to have a greater impact on the total portfolio return compared to the smaller companies in the same portfolio.

3.4 Individual portfolio formation

We create multiple portfolios in order to evaluate each factor. At the end of June each year the size and I/A factor's are decided, while the ROE factor is sorted monthly as in Hou et al. (2015). The BM factor is determined on a monthly basis. The portfolios are created by sorting on size, investment, profitability, and book-to-market. The companies are sorted in ascending order and divided into ten portfolios based on each factor using breakpoints for each 10^{th} percentile, e.g., portfolio 1, 11, 21, and 31 are the low 10% of the ranked values for each factor. One additional portfolio is added where we go long the highest ranked portfolio and short the lowest ranked portfolio, i.e., P10-P1. The portfolio formation is displayed in table 2. The results of the constructed portfolios are then compared to the results obtained when using three factor models, namely: the capital asset pricing model, the Fama-French three-factor model, and the q-factor model.

3.5 Individual factor construction

The individual factor construction follows Fama and French (1993). The size factor (r_{MC}) is a long position on portfolios 1 to 5 and a short position on portfolios 6 to 10, i.e., small

	Small 50%						Big 50%			
	Low 30%			Mid 40%				High 30%		
Size	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Investment	P11	P12	P13	P14	P15	P16	P17	P18	P19	P20
Profitability	P21	P22	P23	P24	P25	P26	P27	P28	P29	P30
Book-to-market	P31	P32	P33	P34	P35	P36	P37	P38	P39	P40

Note: Small 50% and Big 50% are used to create the factor for size. Low 30%, Mid 40%, and High 30% are used to create the factors for investment, profitability, and book-to-market.

Table 2: Portfolios created individually for each factor

minus big. The investment factor ($r_{I/A}$) is a long position on portfolios 11 to 13 and a short position on portfolios 18 to 20, i.e., low minus high. The profitability factor (r_{Roe}) is a short position on portfolios 21 to 23 and a long position on portfolios 28 to 30, i.e, high minus low. And finally, book-to-market (r_{BM}) is a short position on portfolios 31 to 33 and a long position on portfolios 38 to 40, i.e., high minus low.

3.6 Q-factor portfolio formation

Just as in Hou et al. (2015) we construct 18 interaction portfolios with a triple two-by-three-by-three sorting on size, investment, and profitability. At the end of June every year, we use the median to split these companies into two groups based on size. Companies placed in the large and small group respectively, stay there until the next time the portfolios are revised. Then they are free to transfer to the other group if the ranking allows. Independently, at the end of June of year t, we break all stocks into three I/A groups, using the breakpoints for the high 30%, middle 40%, and low 30% of the ranked values of I/A for the fiscal year ending in calendar year $t-1$. Similarly, each month, we sort all stocks into three groups for ROE using the breakpoints for the high 30%, middle 40%, and low 30% of the ranked values of ROE. Table 3 displays the construction of the 18 interaction portfolios used.

3.7 Q-factor factor construction

MC 1^{st} median contain the nine portfolios of the small cap companies and the MC 2^{nd} median contain the nine portfolios of the large cap companies. The size factor in the q-factor model is represented by r_{MC}, which is constructed by subtracting the simple average returns of the nine large portfolios from the simple average returns of the nine small portfolios (small-minus-big), each month. The stocks in the I/A 1^{st} tertile contain the six portfolios with

	ROE 1st tertile	2nd tertile	3rd tertile	I/A
MC 1st median	Portfolio 1	Portfolio 2	Portfolio 3	**1st tertile**
	Portfolio 4	Portfolio 5	Portfolio 6	**2nd tertile**
	Portfolio 7	Portfolio 8	Portfolio 9	**3rd tertile**
MC 2nd median	Portfolio 10	Portfolio 11	Portfolio 12	**1st tertile**
	Portfolio 13	Portfolio 14	Portfolio 15	**2nd tertile**
	Portfolio 16	Portfolio 17	Portfolio 18	**3rd tertile**

Table 3: Portfolio formation based on a triple two-by-three-by-three sorting

the lowest I/A ratio while the I/A 3rd tertile contain the six portfolios with the highest I/A ratio. The investment factor, $\mathrm{r}_{I/A}$, is the difference between the simple average of the returns on the 1st tertile and the simple average of the returns on the 3rd tertile (low-minus-high), each month. The stocks in the ROE's 1st tertile are the six portfolios with the lowest ROE while the ROE's 3rd tertile contain the six portfolios with the highest ROE. The profitability factor, r_{Roe}, is the difference between the simple average of return of the six portfolios with the highest ROE and the simple average of return of the six portfolios with the lowest ROE (high-minus-low), each month. We revise the rankings and sorting of stocks every year in June based on size and I/A. Meanwhile we revise the rankings based on ROE on a monthly basis. The revise is necessary as it is possible for the sampled companies to change rankings due to changes in size, investment, and profitability throughout the year. The procedure to distribute each portfolio based on the three factors follows Hou et al. (2015) and Asad and Cheema (2017).

3.8 Q-factor model

In the model, we denote the excess return for the 18 interaction portfolios as R^i - r^f. The expected excess return is described by the four factors: market execss return (MKT), size factor (r_{MC}), investment factor($\mathrm{r}_{I/A}$), and profitability factor(r_{Roe}). The expression looks as follows,

$$\mathrm{R}_t^i - \mathrm{r}_t^f = \alpha^i + \beta^i_{MKT}\mathrm{MKT}_t + \beta^i_{MC}\mathrm{r}_{MC,t} + \beta^i_{I/A}\mathrm{r}_{I/A,t} + \beta^i_{Roe}\mathrm{r}_{Roe,t} + \epsilon^i \tag{12}$$

in which R^i = expected return on portfolio i; r^f = monthly risk-free rate of return; MKT = monthly market excess return; r_{MC} = a long position on small portfolios and a short position on large portfolios; $r_{I/A}$ = a long position on low-investment portfolios and a short position on high-investment portfolios; r_{Roe} = a long position on high-profitability portfolios and a short position on low-profitability portfolios. α^i is the intercept, β^i_{MKT}, β^i_{MC}, $\beta^i_{I/A}$, and β^i_{Roe} are the regression coefficients of the independent variables, and ϵ is the error term.

3.9 Sensitivity analysis

To validate and create further discussions of the results obtained we performed additional sensitivity tests. Firstly, we test the sensitivity in the interaction portfolios for portfolio weights. This test is done with equally weighted portfolio returns (instead of value-weighted portfolio returns used previously). Secondly, we investigate whether there are any significant differences in returns between the first and the last five-year period.

4 Empirical Result

To evaluate the individual factors, we create multiple portfolios sorted on size, investment, profitability, and book-to-market. Table 4 displays descriptive statistics (monthly average returns and standard deviations) for the 40 portfolios. The findings suggest no mean difference in return for the composed portfolios, except for the high versus low profitability portfolios (1.13%, t = 2.1389). Likewise, the profitability factor turned out to be the only factor significantly different from zero (0.77%, t = 2.4684). Table 5 displays the t-test of the individual factors. With demonstrated significant results, the profitability portfolios where tested and compared using the CAPM, Fama-French three-factor model, and the q-factor model. The estimations received are presented in table 6. When using the CAPM, two portfolios show significant alphas at the 5% level (P23 and P30), while portfolios 21 through 30 displays significant market betas (β_{MC}) at the 5% level. With the Fama-French three-factor model, the same two portfolios (P23 and P30) display significant alphas at the 5% level. Meanwhile all portfolios display significant market betas (β_{MC}) and insignificant size factors (β_{MC}). The BM factor (β_{BM}) is significant in five portfolios. When implementing the q-factor model, two portfolios show significant alphas at the 5% level (P22 and P30), while portfolios 21 through 30 display significant market betas (β_{MC}) at 5% level. Neither when using the q-factor model does any of the portfolios display significant size factors (β_{MC}). The investment factor ($\beta_{I/A}$) is insignificant for all portfolios while the profitability factor (β_{Roe}) is significant in seven portfolios. When implementing the three asset pricing models on P30-P21, the results obtained displayed no significant alphas at the 5% level. However, with the CAPM and the Fama-French three-factor model the alphas were significant at the 10% level which suggest some effect. Although insignificant at the 5% level, the alphas obtained from using the CAPM and the Fama-French three-factor model – 0.92% (t = 1.68) and 0.95% (t = 1.79) on a monthly basis – suggests an economically sizable effect.

With the purpose of evaluating the q-factor model, in the same way as previous research (see e.g., Hou et al., 2015), we created 18 interaction portfolios sorted on size, investment and profitability. Ahead of evaluating the q-factor model we tested each factor's effect on return separately, presented in table 7. The results obtained are similar to the results of the individual factors (the 40 portfolios). Neither the size factor (0.1963%, t = 0.7373) or the investment factor (0.2148%, t = 0.8377) show any significant difference in return at a 5% level. The profitability factor is significantly different from zero, with an average return of 1.40% (t = 4.9559). The aspiration of the thesis was to test if the q-factor model could summarize the cross-section of average stock returns on the Swedish market, as Hou et al. (2015) did on the US market, and to what extent. However, as only the profitability factor proved to be significant at the 5% level, it leaves us unable to further evaluate the model and our presented research question. Descriptive statistics (monthly average returns and standard deviations) of the 18 interaction portfolios are presented in table 8.

Portfolio	**Mean**	**SD**	**Portfolio**	**Mean**	**SD**
1	0.007659	0.064645	11	0.014512	0.072133
2	0.011223	0.055670	12	0.017345	0.053249
3	0.010261	0.056670	13	0.011525	0.049923
4	0.012048	0.055743	14	0.007421	0.049427
5	0.012542	0.056311	15	0.008782	0.042223
6	0.012770	0.053774	16	0.010444	0.050073
7	0.013677	0.053747	17	0.004206	0.053231
8	0.013247	0.048429	18	0.011798	0.047145
9	0.012840	0.043670	19	0.010223	0.047334
10	0.008343	0.038911	20	0.011062	0.059890
21	0.004691	0.060023	31	0.011427	0.045819
22	0.009350	0.061092	32	0.011070	0.048735
23	0.002745	0.051640	33	0.007822	0.046148
24	0.008733	0.048509	34	0.010311	0.051956
25	0.005962	0.044579	35	0.009802	0.047581
26	0.011964	0.048366	36	0.005641	0.047240
27	0.009293	0.046589	37	0.008336	0.050847
28	0.010973	0.051482	38	0.015327	0.054042
29	0.012836	0.049023	39	0.013236	0.052085
30	0.016028	0.051347	40	0.011543	0.054630

Table 4: Individual portfolios

	Mean	**Std. Error**	**t**	$\mathbf{r}_{MC}$	$\mathbf{r}_{I/A}$	$\mathbf{r}_{Roe}$	$\mathbf{r}_{BM}$
$\mathbf{r}_{MC}$	-0.001429	0.002360	-0.6055	1.0000			
$\mathbf{r}_{I/A}$	0.003433	0.003231	1.0626	-0.1318	1.0000		
$\mathbf{r}_{Roe}$	0.007684	0.003113	2.4684	-0.1926	-0.0912	1.0000	
$\mathbf{r}_{BM}$	0.003262	0.002446	1.3338	0.1651	-0.0651	-0.2597	1.0000

Table 5: Factor t-test and correlation matrix for individual factors

	Portfolio	P21	P22	P23	P24	P25	P26	P27	P28	P29	P30	P30-P21
CAPM	α	-0.0034	0.0004	-0.0069*	-0.0010	-0.0029	0.0019	-0.0001	0.0004	0.0031	0.0062*	0.0092
		(0.0048)	(0.0047)	(0.0030)	(0.0024)	(0.0025)	(0.0021)	(0.0022)	(0.0025)	(0.0025)	(0.0026)	(0.0055)
	β_{MKT}	0.8270*	0.9208*	0.9916*	1.0046*	0.9059*	1.0370*	0.9641*	1.0900*	1.0075*	1.0094*	0.1832
		(0.1121)	(0.1486)	(0.0669)	(0.0467)	(0.0765)	(0.0600)	(0.0530)	(0.0691)	(0.0671)	(0.0878)	(0.1426)
	R^2	0.3180	0.3803	0.6174	0.7164	0.6925	0.7713	0.7165	0.7513	0.7078	0.6464	0.0167
FF three-factor	α	-0.0033	0.0002	-0.0072*	-0.0011	-0.0034	0.0020	0.0001	0.0004	0.0034	0.0067*	0.0095
		(0.0048)	(0.0048)	(0.0029)	(0.0023)	(0.0025)	(0.0021)	(0.0022)	(0.0024)	(0.0025)	(0.0025)	(0.0053)
	β_{MKT}	0.8259*	0.8882*	0.9350*	0.9811*	0.8336*	1.0413*	0.9919*	1.1089*	1.0519*	1.0848*	0.2604*
		(0.1084)	(0.1493)	(0.0748)	(0.0490)	(0.0753)	(0.0601)	(0.0531)	(0.0738)	(0.0701)	(0.0877)	(0.1260)
	β_{MC}	0.2060	0.0909	0.0896	0.0865	-0.1027	0.0325	0.0528	-0.1894*	0.0619	0.0197	-0.1792
		(0.2038)	(0.1411)	(0.1124)	(0.1024)	(0.0868)	(0.0819)	(0.0769)	(0.0931)	(0.0851)	(0.1160)	(0.2427)
	β_{BM}	0.0463	0.1753	0.2907*	0.1305	0.3278*	-0.0142	-0.1234	-0.1287	-0.2018*	-0.3595*	-0.4078*
		(0.1765)	(0.1776)	(0.1264)	(0.0899)	(0.1144)	(0.0856)	(0.0832)	(0.1343)	(0.1025)	(0.0927)	(0.1948)
	R^2	0.3269	0.3882	0.6424	0.7244	0.7266	0.7716	0.7211	0.7667	0.7185	0.6774	0.0604
q-factor	α	0.0023	0.0075*	-0.0044	-0.0006	-0.0038	0.0015	0.0004	-0.0011	0.0013	0.0053*	0.0026
		(0.0036)	(0.0032)	(0.0029)	(0.0024)	(0.0024)	(0.0021)	(0.0024)	(0.0024)	(0.0024)	(0.0026)	(0.0040)
	β_{MKT}	0.9429*	1.0346*	1.0421*	1.0141*	0.9093*	1.0461*	0.9721*	1.0513*	0.9867*	0.9816*	0.0396
		(0.0781)	(0.0920)	(0.0730)	(0.0488)	(0.0747)	(0.0636)	(0.0508)	(0.0601)	(0.0586)	(0.0851)	(0.0966)
	β_{MC}	0.0041	0.1513	0.0563	0.0991	0.0006	0.0497	0.0112	-0.1643	0.0949	-0.0216	-0.0196
		(0.1591)	(0.1302)	(0.1130)	(0.1074)	(0.0983)	(0.0800)	(0.0814)	(0.0862)	(0.0843)	(0.1142)	(0.1704)
	$\beta_{I/A}$	0.0608	-0.1290	0.0189	-0.0066	0.1563	0.1136	-0.0093	-0.0436	0.0777	-0.0834	-0.1470
		(0.1061)	(0.1667)	(0.0686)	(0.0786)	(0.0801)	(0.0837)	(0.0786)	(0.0581)	(0.0672)	(0.1068)	(0.1671)
	β_{Roe}	-0.9171*	-1.0398*	-0.3844*	-0.0474	0.0436	-0.0052	-0.0660	0.2404*	0.2371*	0.1813*	1.0979*
		(0.1304)	(0.1085)	(0.0965)	(0.0706)	(0.0852)	(0.0668)	(0.0659)	(0.0702)	(0.0653)	(0.0836)	(0.1319)
	R^2	0.5877	0.6968	0.6843	0.7209	0.7082	0.7784	0.7190	0.7887	0.7347	0.6654	0.4424

Note: Standard errors are given within parentheses. * denotes significance at the 5% level or better

Table 6: CAPM, Fama-French three-factor model and the q-factor model

	Mean	**Std.Error**	**t**	$\mathbf{r}_{MC}$	$\mathbf{r}_{I/A}$	$\mathbf{r}_{Roe}$
$\mathbf{r}_{MC}$	0.001963	0.002663	0.7373	1.0000		
$\mathbf{r}_{I/A}$	0.002148	0.002564	0.8377	-0.3044	1.0000	
$\mathbf{r}_{Roe}$	0.013993	0.002824	4.9559	-0.2049	0.2457	1.0000

Table 7: Factor t-test and correlation matrix

Portfolio	**Mean**	**SD**	**Portfolio**	**Mean**	**SD**
1	-0.001378	0.070251	10	0.020269	0.063404
2	0.015355	0.056911	11	0.009135	0.046976
3	0.024641	0.069507	12	0.018291	0.059566
4	-0.000614	0.060861	13	0.000573	0.060799
5	0.011687	0.055532	14	0.007659	0.041681
6	0.023976	0.055079	15	0.010690	0.050145
7	0.007285	0.100940	16	0.006164	0.069386
8	0.011206	0.057549	17	0.010113	0.048275
9	0.023532	0.060622	18	0.015126	0.047390

Table 8: Descriptive statistics: Two-by-three-by-three

4.1 Discussion

As displayed in table 4, the individually composed profitability portfolios show sign of mean difference in return, while the 18 interaction portfolios show no significant variation in the return over the 10-year period. With mostly insignificant results, only trivial conclusions could be drawn from our findings. The results could however be discussed in consultation with our presented hypothesis which are closely aligned with three well-documented relations: (i) market capitalization-expected return relation, (ii) investment-to-asset-expected return relation, and (iii) profitability-expected return relation. As such, the following discussion renders whether we are able to depict any such relations from our results.

When examining (i) the market capitalization-expected return relation, our findings are ambiguous. With the individual portfolio construction our findings suggest that the small sized portfolios generate on average smaller return than the large sized portfolios (0.14%, t = 0.6055). When examining the 18 interaction portfolios the MC 1^{st} median (small size firms) generate greater average return than the corresponding portfolios within the MC 2^{nd} median (large size firms), but insignificant at the 5% level (0.20 %, t = 0.7373). Consequently, with reference to our results, we are not able to reject our first hypothesis. It comes as no surprise as in recent years, research on both US and international data suggests that there no longer exists a size effect (e.g., Eleswarapu and Reinganum, 1993; Dichev, 1998, Amihud, 2002) and that many anomalies are hard to replicate after discovery (Hirshleifer, 2001; Hou et al., 2018).

The argument concerning (ii) investment-to-asset-expected return relation, advocates that there is a negative investment-return relation conditional on expected profitability. The results obtained have some patterns in line with previous research; however, only scarce analyses should be implemented. The results of the individual portfolio construction (0.34 %, t = 1.0626) and the 18 interaction portfolios (0.21%, t = 0.8377) suggests that companies with low investment generate greater expected return, however, not significant at the 5% level. One significant difference in mean return was found between the 1^{st} and the 2^{nd} I/A tertile (0.54%, t = 2.4203). Altogether, our findings are insignificant and as such we are unable to reject hypothesis 2. Interestingly, the results have patterns that are in line with findings of previous literature and the negative investment-return relation mentioned. In four out of six occasions did the negative investment-to-asset-expected return relation hold given a certain level of profitability. As for the size factor, our findings of the I/A factor is ambiguous and no further conclusions should be drawn from insignificant results.

The findings obtained concerning the (iii) profitability-expected return relation, can be attributed to the literature on profitability and its effect on expected return. As mentioned in Hou et al. (2015) "The profitability-expected return relation is consistent with momentum, post- earnings-announcement drift, and the financial distress effect" (p.657). Research suggests that firms with high profitability should earn higher expected returns and vice versa given a certain level of investment-to-asset. That is, having a positive profitability-expected return relation being conditional on investment-to-asset. With our findings we depict such positive profitability-expected return relation also on the Swedish equity market from July 2010 to June 2020. The profitability factor (r_{Roe}) is significant at the 5% level, both for the individual portfolio construction and for the 18 interaction portfolios. Out of the 18 interaction portfolios, the tertile containing the high ROE did in five out of six occasions generate the greatest expected return for a given investment-to-asset level. In respect to visible relations and significant profitability factors we are able to reject our third hypothesis and we can start to believe that there is a positive profitability-expected return relation. There is also a mean difference in average return on the individual portfolio level when comparing P30 to P21 (displayed in A3) which adds credibility to the suggested positive profitability-expected return relation also found in Novy-Marx (2013) and Hou et al. (2015).

Portfolios	**Mean**	**Std. Error**	**t**
MC 1^{st} - MC 2^{nd}	0.001963	0.002663	0.7373
I/A 1^{st} - I/A 2^{nd}	0.005390	0.002227	2.4203
I/A 2^{nd} - I/A 3^{rd}	-0.003243	0.002346	-1.3823
I/A 3^{rd} - I/A 1^{st}	-0.002148	0.002564	-0.8377
ROE 1^{st} - ROE 2^{nd}	-0.005476	0.002664	-2.0559
ROE 2^{nd} - ROE 3^{rd}	-0.008517	0.001662	-5.1259
ROE 3^{rd} - ROE 1^{st}	0.013993	0.002824	4.9559

Table 9: Mean difference in MC, I/A, and ROE portfolios

4.2 Sensitivity analysis results

The first sensitivity test implemented is a test for the weight allocation in the interaction portfolios. Neither when using equally weighted portfolios were the size factor or the investment factor significant at the 5% level as displayed in table 10. The size factor earns an average return of 0.14% (t = 0.6039) and the investment factor earns an average return of 0.27% (t = 1.2635). Similar to the value weighted portfolios, the profitability factor is significant and earns an average return of 2.19% (t = 8.5007).

The second sensitivity test implemented concerned whether there were any significant differences in returns between the first and the last five-year period. The results are displayed in table 11. Neither with the two different time periods were we able to test the q-factor model due to some insignificant results on the factor level. However, the size factor in the last five year period proved to be significantly different from zero (0.69%, t = 2.0450). Likewise, the profitability factor earned an average return of 1.67% (t = 3.9768) in the first five-year period and 1.13% (t = 2.9882) in the last five-year period.

	Mean	**Std.Error**	**t**	$\mathbf{r}_{MC}$	$\mathbf{r}_{I/A}$	$\mathbf{r}_{Roe}$
$\mathbf{r}_{MC}$	0.001363	0.002257	0.6039	1.0000		
$\mathbf{r}_{I/A}$	0.002710	0.002145	1.2635	-0.0739	1.0000	
$\mathbf{r}_{Roe}$	0.021914	0.002578	8.5007	-0.1782	0.1164	1.0000

Table 10: Factor t-test and correlation matrix on two-by-three-by-three sorted equally weighted portfolios

	Mean	**Std. Error**	**t**	$\mathbf{r}_{MC}$	$\mathbf{r}_{I/A}$	$\mathbf{r}_{Roe}$
Year 1-5						
r_{MC}	-0.003006	0.004035	-0.7451	1.0000		
$r_{I/A}$	0.007373	0.004004	1.8414	-0.2520	1.0000	
r_{Roe}	0.016653	0.004188	3.9768	-0.2679	0.2450	1.0000
Year 6-10						
r_{MC}	0.006933	0.003390	2.0450	1.0000		
$r_{I/A}$	-0.003078	0.003092	-0.9955	-0.3275	1.0000	
r_{Roe}	0.011333	0.003793	2.9882	-0.0964	0.2213	1.0000

Table 11: Factor t-test and correlation matrix for the first and final 5-year period

5 Conclusion

In conclusion, the triple two-by-three-by-three sorted portfolios, that is implementing the q-factor model, is not applicable on the Swedish equity market for the time period 2010 to 2020. Unlike previous research, see e.g., Hou et al. (2015) examination on the US market, we are unable to depict any cross-sectional variation in average stock returns. We are however able to provide evidence for a positive profitability-expected return relation. Although trivial, the findings of this study serves as an extension, albeit modest, to the existing literature of the q-factor model. With the previously unexplored Swedish market, our research serves as a credibility tool for the q-factor model in a changing setting.

5.1 Limitations

As the q-factor model is in reduced form, *equation 12* is limited to take co-movements of factors into account. In order to fully grasp and allow for the co-movements between the factors, one need to surpass the limits of the q-factor model. Instead, one would need to specify a dynamic investment model to take into account sources of cross-sectional heterogeneity in factor loading's of investment and profitability. Although it being a valid point for other research, our insignificant findings on individual factor level prevented us from testing the proposed q-factor model in this research.

Another limitation stem from COMPUSTAT that provides the accounting information in the study. As displayed in table 1, there are some missing values in the sample which possibly might have had an effect on the outcome. Finding an alternative source of information and/or additional databases to limit the amount of missing values is crucial for better trustworthy results.

5.2 Future research

As we were unable to validate the q-factor model, it would have been interesting to see how the results would have differed if one where to change the time frame used. In addition to the time aspect, it would also be interesting to include other countries, as well as implementing the augmented q-factor model presented in Hou et al. (2020) and comparing the results.

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A Appendix

Portfolio	P1	P2	P3	P4	P5	P6
α	-0.0123*	0.0052	0.0140*	-0.0081	0.0013	0.0135*
	(0.0047)	(0.0034)	(0.0045)	(0.0048)	(0.0034)	(0.0030)
β_{MKT}	1.1274*	1.0491*	1.1000*	0.7567*	1.0705*	1.0771*
	(0.1228)	(0.0765)	(0.1437)	(0.1326)	(0.1140)	(0.0604)
R^2	0.4311	0.5683	0.4203	0.2581	0.6234	0.6404

Portfolio	P7	P8	P9	P10	P11	P12
α	-0.0027	0.0008	0.0138*	0.0133*	-0.0001	0.0077*
	(0.0088)	(0.0036)	(0.0044)	(0.0049)	(0.0026)	(0.0037)
β_{MKT}	1.0287*	1.0799*	0.9998*	0.7031*	0.9481*	1.0934*
	(0.2382)	(0.0911)	(0.1214)	(0.1314)	(0.0627)	(0.1165)
R^2	0.1737	0.5883	0.4548	0.2072	0.6821	0.5651

Portfolio	P13	P14	P15	P16	P17	P18
α	-0.0093*	-0.0017	0.0003	-0.0046	0.0005	0.0063*
	(0.0045)	(0.0012)	(0.0023)	(0.0045)	(0.0025)	(0.0026)
β_{MKT}	1.0139*	0.9610*	1.0714*	1.1171*	0.9870*	0.9089*
	(0.1194)	(0.0317)	(0.0523)	(0.1175)	(0.0580)	(0.0720)
R^2	0.4651	0.8906	0.7655	0.4341	0.7006	0.6165

Note: Standard errors are given within parentheses. * denotes significance at the 5% level or better

Table A1: CAPM regression analysis on two-by-three-by-three

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16	P17	P18
P1	1.0000																	
P2	0.6403	1.0000																
P3	0.6163	0.6163	1.0000															
P4	0.5656	0.5388	0.4398	1.0000														
P5	0.6838	0.7628	0.6873	0.5913	1.0000													
P6	0.6196	0.7439	0.6591	0.5232	0.7643	1.0000												
P7	0.4481	0.3933	0.4785	0.4575	0.4012	0.4256	1.0000											
P8	0.6626	0.6663	0.5961	0.5484	0.7637	0.6881	0.4335	1.0000										
P9	0.5884	0.6757	0.5835	0.4927	0.7178	0.6572	0.4020	0.7077	1.0000									
P10	0.4282	0.3894	0.2970	0.2128	0.3621	0.3532	0.1589	0.3958	0.3213	1.0000								
P11	0.5449	0.6249	0.4903	0.3845	0.6403	0.6757	0.3301	0.5974	0.4763	0.3987	1.0000							
P12	0.5266	0.6077	0.4817	0.3352	0.6025	0.6287	0.3291	0.5686	0.4607	0.4031	0.6570	1.0000						
P13	0.4113	0.5817	0.3175	0.3787	0.5337	0.5683	0.2815	0.5078	0.4773	0.3387	0.5022	0.4552	1.0000					
P14	0.6271	0.7000	0.6126	0.4892	0.7702	0.7881	0.4326	0.7273	0.6501	0.3905	0.7492	0.6956	0.6839	1.0000				
P15	0.5921	0.6472	0.5909	0.3506	0.6881	0.6866	0.3106	0.6796	0.5687	0.4017	0.6930	0.6554	0.6071	0.8400	1.0000			
P16	0.5664	0.6018	0.4967	0.4634	0.6043	0.5980	0.4285	0.6073	0.5560	0.3713	0.5200	0.4630	0.4316	0.6205	0.5295	1.0000		
P17	0.5355	0.7170	0.5638	0.4681	0.6848	0.6623	0.3248	0.6534	0.5811	0.3758	0.6675	0.6452	0.5518	0.7630	0.6844	0.5360	1.0000	
P18	0.5077	0.6089	0.5667	0.4395	0.6001	0.6415	0.3329	0.6077	0.5777	0.3726	0.5534	0.5135	0.5482	0.7083	0.6136	0.5441	0.6822	1.0000

Table A2: Correlation matrix on two-by-three-by-three

Portfolios	**Mean**	**Std. Error**	**t**
P10-P1	0.000684	0.004809	0.1423
P20-P11	-0.003450	0.007423	-0.4647
P30-P21	0.011337	0.005300	2.1389
P40-P31	0.000116	0.003967	0.0293

Table A3: Mean difference in individual portfolios

Portfolio	**Mean**	**SD**	**Portfolio**	**Mean**	**SD**
1	0.000465	0.073217	10	0.008303	0.067440
2	0.016991	0.055062	11	0.011331	0.049996
3	0.027040	0.066494	12	0.022234	0.051929
4	-0.002302	0.055945	13	-0.000673	0.060799
5	0.013632	0.052686	14	0.011361	0.041681
6	0.020087	0.062305	15	0.017364	0.050145
7	-0.002880	0.052383	16	0.000387	0.069386
8	0.012355	0.047598	17	0.012182	0.048275
9	0.028712	0.049066	18	0.019347	0.047390

Table A4: Descriptive statistics: Two-by-three-by-three sorted equally weighted portfolios