LUND UNIVERSITY

SCHOOL OF ECONOMICS AND MANAGEMENT

Department of Economics
NEKN02
Master thesis
June 2023

Decoding the Winning Strategy

An in-depth study of Swedish closed-end funds

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Abstract

The predictability of stock returns, prediction of buyout targets and value creation by activist owners are well-researched areas. However, Swedish closed-end funds' outstanding performance has received little attention. By implementing the existing research, we explore the key characteristics of closed-end fund targets and determine if investing in these characteristics can outperform the market. We investigate 215 transactions over the last decade and examine key performance indicators at purchase to find what distinguishes closed-end fund targets. Compared to the Swedish equity market, we discovered that closed-end funds invest in companies with lower valuations but higher profitability, efficiency, growth, number of analyst recommendations, and interest coverage ratios. At the same time, we cannot find differences in leverage.

Furthermore, we trained a logit model on these characteristics to make predictions and form synthetic closed-end fund portfolios. We invested equally in the 15 most probable equities picked by the model to implement a buy-and-hold strategy over various periods. The strategy significantly outperformed the Swedish equity market in 67% of the time periods. We also did an out-of-sample test and cannot conclude the same results for the US market with consistent underperformance. To summarise, we present evidence that closed-end funds distinguish themselves from the rest of the market by investing in companies with specific financial characteristics. The results further imply that the CEFs target well-managed companies with good operating performance instead of low-performing companies with much room for improvement. We have also proved that it is possible to build a synthetic CEF portfolio from these characteristics and outperform the market. This is given that the model is trained on factors implemented by the leader in the particular market where the model picks companies. Conclusively we have also managed to create a strategy which has practical usability for a retail investor since all information origins from public market data.

Acknowledgements: We would like to express our gratitude to our supervisor, Jens Forssbaeck, for his support and guidance throughout the writing of this thesis and being available throughout the entire process.

Keywords: Closed-end funds, predictability of stock returns, predicting investor targets, active ownership.

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1 Introduction

What in Swedish is called *investmentbolag* is a popular savings vehicle by Swedish retail investors. In fact, the by far most owned stock on the largest online retail broker, Avanza, is Investor with almost 350k owners, with also Kinnevik and Latour on the top ten list (Avanza, 2023). The format dates back to the 1910s-1930s when, e.g., Investor, Kinnevik, and Industrivärden were listed on the stock market. We will hereafter name them closed-end funds, or CEFs, since it is the closest English definition with the same characteristics. Unlike a regular mutual fund, CEFs issue capital through an initial public offering and can then increase or decrease capital by issuance of new stock or debt, distribution to shareholders, and performance of its investments (Fidelity Investments, 2012). The portfolio managers will then invest the firm's funds in public and private equities, or other assets such as bonds and real estate. According to Fidelity Investments (2012), the CEFs, compared to a mutual fund, benefit from not having reinvestment risk from daily share issuances and not having to hold excess cash to meet outflows.

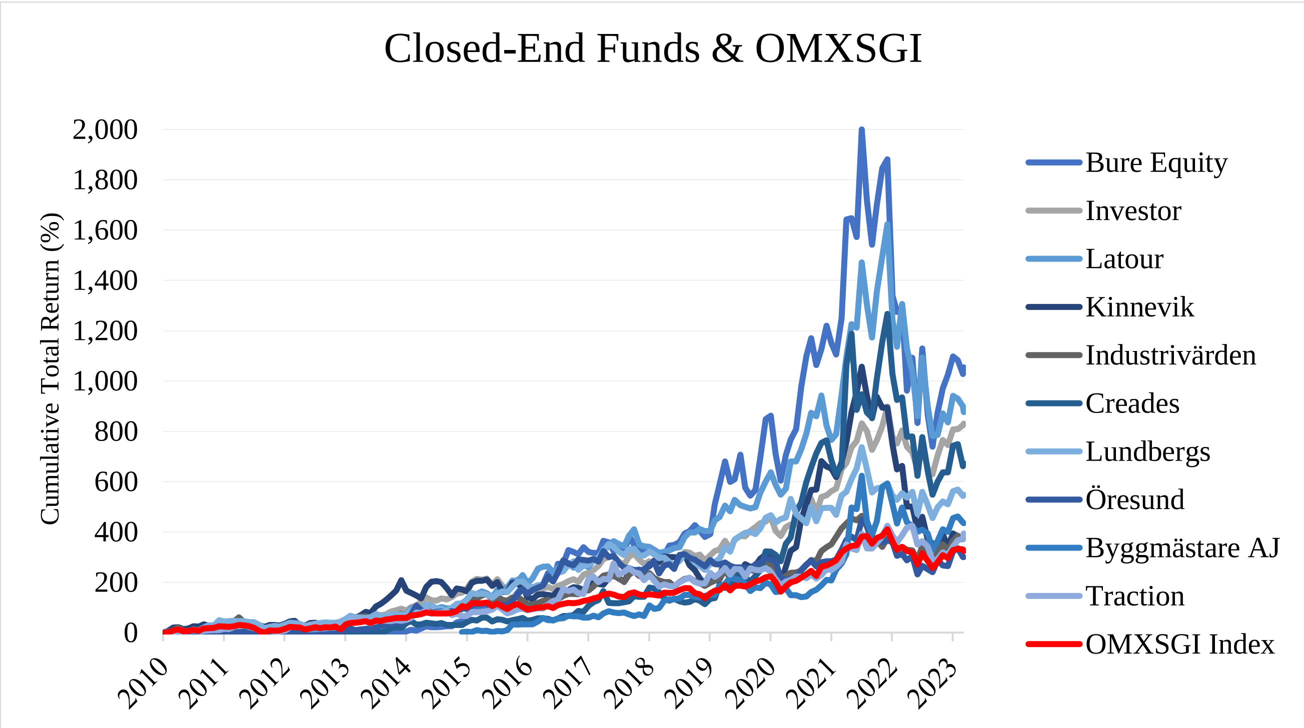

Figure (1): Closed-End Funds and Index Comparison

It is easy to understand why investing in the CEFs has been popular when looking at their performance and value creation. Figure (1) above shows the cumulative return over our sample of the last 13 years with reinvested dividends for the CEFs, compared to the broad Swedish stock index OMXSGI. Even over a more extended period, such as 20 years, the CEFs outperform the OMXSGI (Bloomberg, 2023). The index includes all shares listed on Nasdaq OMX Stockholm, assuming dividends to be reinvested (Nasdaq OMX, 2023). Because of the significant outperformance compared to the market, studying possible explanations and what distinguishes the CEFs' strategies is interesting. We want to investigate if CEFs are taking higher risks or are skilled stockpickers with a successful strategy and characteristics that a retail investor can replicate to beat the market.

Closed-end funds can create value by buying firms with specific characteristics or actively improving the businesses. It may be a combination of both, but we will only examine the first argument. This distinction is made since an individual investor cannot often replicate active ownership, as it requires significant capital. Another restriction is that CEFs generally invest in both private and public companies. Since a retail investor has limited access to the private equity market, we only consider public holdings. However, the CEFs included in this study have a majority of assets under management in public companies, ensuring that the listed portion played a significant role in historical value creation. The distribution can be seen in Figure (2) below.

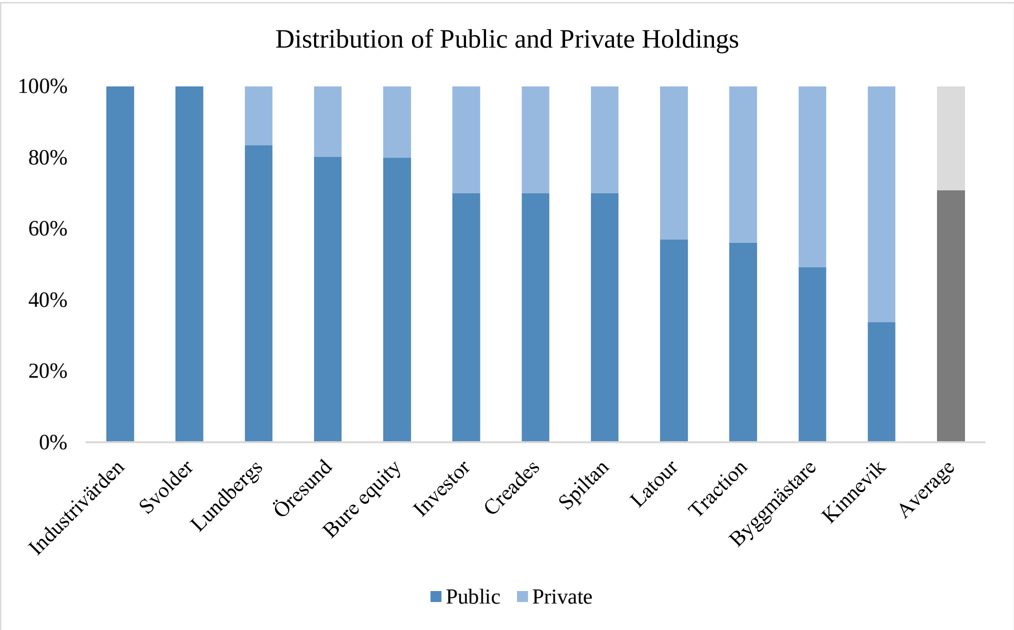

Figure (2): Closed-end fund's distribution of public and private holdings as of 2022

Furthermore, we aim to study the strategy Swedish CEFs use for their public equity portfolios with the purpose of creating a replicating method for retail investors. We will quantify the strategy by evaluating a broad spectrum of financial ratios of CEF targets and non-targets covering valuation, efficiency, profitability, leverage, and other relevant measures. Targets will be defined as companies that CEFs have bought, and non-targets are all other stocks on Nasdaq OMX Stockholm. Swedish CEFs have a track record of substantially outperforming the market; therefore, a quantitative study is highly relevant to find possible explanations. The purpose of this thesis is to answer the following research question.

> What firm characteristics represent a typical CEF target in the public equity market, and can we use these characteristics to build a synthetic equity portfolio and outperform the market?

Therefore, we will evaluate if value creation in the public equity portfolio is connected to specific company characteristics or if the value is created by, for example, active ownership. We will also study if the CEFs target better-than-average companies or if the strategy is to develop bad-performing companies.

Our method starts with a qualitative assessment of the CEFs' communicated strategies and investment criteria. These are later used to select quantitative measures and ratios, which we compare between the target and non-target groups to find differences. Significant results were used to decide which predictors to use and then form synthetic CEF portfolios with a logit model. These portfolios will consist of equities which, according to our model, are the most probable hypothetical targets for CEFs in the Swedish market. The portfolios will then be evaluated with various performance measures and benchmarked against the market portfolio. To test the strategy out-of-sample and on a completely different market, we will also implement our strategy on the S&P 500.

To summarise, we provide evidence that the CEFs buy companies with lower valuations but higher profitability, efficiency, growth, number of analyst recommendations, and interest coverage ratio. At the same time, we cannot find differences in leverage. In addition, our replicating strategy has significantly outperformed the Swedish market in 67% of the time periods. In addition, we performed robustness tests by changing the portfolio size and still managed to beat the Swedish market. The same cannot be concluded for the US market as the portfolios underperform the market for various reasons, such as index composition, as the Swedish market differs from the US market.

The literature on predicting stock returns, buyout targets, and activist targets is extensive, with various well-established methods. However, we have found a gap in the literature regarding closed-end funds and a lack of understanding of what drives value in their public equity portfolios. This is particularly interesting due to the immense performance over time, seen in

Figure (1). Even if our study is focused on Swedish CEFs, we complement the wider research areas within the efficient market hypothesis and predictability of stock returns by outperforming the market with only historical financial data. Furthermore, by combining the methods to predict targets and use company characteristics to predict stock returns, we enlarge the existing literature and provide an understanding of the value creation in CEFs. By studying the investor group CEFs, we discuss the importance of active ownership in value-creation, which complements existing research mainly covering activist hedge funds. Moreover, it is also possible for a retail investor to implement the strategy and models we present, which creates practical usability for the individual investor to follow a winning strategy and potentially outperform the market.

The thesis will start with a summary and review of the previous literature in chapter two. Chapters three and four will describe the collection of data and a detailed description of the method, and chapters five, six, and seven present empirical findings, analysis, and conclusions.

2 Literature Review

This chapter will present the previous research and theories laying the foundation of the thesis. The research around value creation in closed-end funds is relatively thin. However, CEFs have similar characteristics to several other investor types, e.g., private equity, hedge funds, and mutual funds, which allow us to explore adjacent research areas. We will begin with a historical review surrounding the efficient market hypothesis and studies which confirm but also challenge the theory by providing evidence of the predictability of stock returns. The second part will address the predictability of private equity targets, while the last part will present the value-creation of activist owners to understand the excess returns of Swedish CEFs better. Since our goal is to successfully extract a strategy from the CEFs to outperform the stock market, we hope to contribute to the literature on the predictability of stock returns and investment targets and expand the literature around value creation in CEFs.

Kendall (1953) showed that stock prices are random, which laid the ground for the random walk and efficient market hypotheses. **Fama's (1970)** influential article Efficient Capital Markets later concluded that the evidence of efficient markets is extensive, which implies that all new information will immediately be incorporated into the stock price. This means that neither technical nor fundamental analysis then would work to predict stock prices. **Malkiel (2003)** suggested that the best way to test the efficient market hypothesis is to compare actively managed funds with comparable stock indices. His study shows that fund managers, on average, underperform the stock market, implying insufficient predictability of future prices. However, as seen in Figure (1), all Swedish closed-end funds in our sample except one have outperformed a broad index over the last 13 years. We, therefore, intend to contribute to the research area by creating a replicable strategy to beat the stock market.

Malkiel (2003) points out that the efficient market hypothesis began to be far less accepted by the beginning of the twenty-first century. He mentions research strengthening technical predictability, such as short-term momentum effects and long-term reversal to the mean, but also fundamental predictability by buying lower-valued stocks. **Ou and Penman (1989)** analysed over 60 financial measures to predict stock returns, e.g., Profit margins, Operating Return on Assets, and Debt/Equity. They found that selected ratios had predictive power of future stock returns, implying that the characteristics of the CEF targets may explain some of the overperformance. **Fluck et al. (1997)** showed that investing in the lowest Price/Earnings decile on the US market overperformed by 1,4x. Also, a low Price/Book strategy generated significant excess returns, while the authors could not prove that either low- or high-growth stocks perform differently than the market. In line with the above, **Lewellen (2004)** found predictive ability in the valuation metrics Price/Book, Earnings yield, and Dividend yield. By studying the CEFs, we want to see if the same ratios can explain their performance or if other variables have higher explanatory power.

Since we view the CEFs as leading stock pickers in the Swedish public equity market, a study made by **Dittmar and Nain (2012)** is relevant. The study concluded that acquirers who purchased companies where a financial buyer participated in the bidding showed abnormal returns compared to those who purchased companies with only corporate bidders. Financial buyers are known for being experts in finding targets with much room for operational improvements and therefore undervalued by the market. In contrast, operational synergies are often the main interest of corporate acquirers (Dittmar & Nain, 2012). Our study does not aim to buy the same companies as the CEFs but instead targets to replicate the CEF's overarching investing strategy to outperform the stock market.

The research field of predicting takeover targets has laid the theoretical foundation for our prediction of CEF targets. **Maupin et al. (1984)** were among the first to study the financial characteristics of buyout targets. The study concludes several significant differences in targeted companies: lower Price/Book, stable and high Dividend yield, high insider ownership, and high cash flow. **Loh (1992)** used a binary logit model based on financial characteristics to find that a typical leveraged buyout (LBO) candidate has higher debt levels, operates more efficiently in terms of turnover ratio, and has a higher level of free cash flow. **Wilson et al. (2022)** state that UK private equity (PE) firms target cash-generative companies with high interest coverage ratios. Contradicting Loh, Wilson et al. found that PE firms target companies with lower productivity to improve performance and growth after the acquisition. Following the mentioned research, we intend to increase awareness of the characteristics targeted by CEFs.

Free cash flow (FCF), mentioned in Loh (1992) above, is defined as in **Jensen (1986)**: the available cash in excess of what is needed to fund all positive net present value (NPV) projects. The theory implies that firms with high levels of FCF are more likely to do low or negative NPV projects due to agency problems between shareholders and management. According to Jensen's theory, there are two probable takeover targets. First, companies with bad performance due to lousy management teams, and second, companies that have performed well but refuse to pay out excess cash to the shareholders. The theory is relevant in our study since we want to understand if the CEFs create value by investing in already great companies or where there is room for improvement. Jensen also points out that the firms do not need to be taken over to increase efficiency and payouts to shareholders. The takeover threat can also trigger the management to perform in the interest of shareholders. We have seen several examples of CEFs buying out entire companies, e.g., Bure's purchase of Allgon in 2021 (Bure Equity, 2021).

Clifford (2008) discusses how agency problems can be solved by having large shareholders as monitors. According to the author, however, few empirical studies have shown that pension funds, mutual funds and other institutional investors manage to increase share value or operating performance. Clifford mentions how hedge funds differ because of performance-based compensation, lockup of investor capital, i.e., no need to hold liquidity as mutual funds do, less regulation, and use of leverage, which can increase the incentives to monitor well. Also, the possibility or threat to buy the entire firm might incentivise the management to perform in line with the shareholder's best interest. According to Clifford, these factors make hedge funds more likely to create value through active ownership. We see many of the same features in the CEFs. Therefore, discussing whether the value creation is due to buying specific company characteristics or by active ownership is essential. Clifford's study shows significant excess returns in 12, 24, and 36 months after the investment for activist hedge funds. Clifford also showed that firms targeted by activist hedge funds increased their Return on Assets (ROA) in the year following the investment. This was primarily done by decreasing assets with cash flows relatively unchanged. Clifford also showed that activist hedge funds targeted firms with lower cash levels and similar payout ratios, which indicates that the activists do not raid companies for large payouts at the expense of long-term value. The study also concludes that hedge funds with longer lockups, i.e., better ability to invest long-term without the risk of cash outflow from the fund, are more likely to engage in activism. Since CEFs have similar characteristics, as the capital base is permanent, we find research on activist hedge funds relevant.

Later research shows results broadly in line with Clifford (2008). Activists target companies that are smaller than peers, with lower valuation, but with higher ROA (**Brav et al., 2008; Carrothers, 2017; Aslan & Kumar, 2016**). Brav et al. also showed that the targets have higher analyst coverage, while **Greenwood and Schor (2009)** instead showed that they target less covered companies with worse than industry stock performance. Further, **Boyson and Mooradian (2011)** and Aslan and Kumar (2016) showed that the targets have lower-than-average revenue growth. The research also indicates that activists receive higher returns than non-activists (Brav et al., 2008; Boyson & Mooradian, 2011). This signals that the CEF's value creation might not only be from picking better stocks but also from active ownership and improving their holding companies. We intend to provide the reader with evidence of if the CEFs target company characteristics in-line with the activist funds' targets.

Our literature review has resulted in three hypotheses, as seen in Table (1) below. The efficient market hypothesis has laid the foundation since the intuition is that it should not be possible to beat the market with only historical financial data. The CEFs' long-term overperformance opens the discussion of if their winning strategy stems from better stock picking based on financial ratios or, for example, active ownership to improve the companies, which is harder to replicate. In addition, previous research on the characteristics of buyouts and activist targets has inspired the first hypothesis since we want to find what characteristics distinguish the CEFs' strategies. The same research fields have influenced the second hypothesis, where a few studies show that other investor groups target companies with worse operating performance. The efficient market hypothesis and the research on predicting stock returns have laid the ground for the third hypothesis since previous research has found successful strategies for investing based on specific financial ratios.

Hypotheses	
$H0_1$	We cannot find significant differences between targets and non-targets regarding financial ratios.
$H0_2$	CEFs do not target well-managed companies with better operating performance than the market average, and hence limited potential for improvements through active ownership.
$H0_3$	We cannot create excess returns by composing portfolios with specific financial characteristics similar to what CEFs generally include in their portfolios.

Table 1: Hypotheses

3 Data

3.1 Selection of CEF Sample

The study's sample of target companies originates from the transactions of 12 listed CEFs, further described in Appendix (1). We have chosen to only look at listed CEFs since they have publicly available transaction data and communicate their strategies. Additionally, we have made two exclusions. We do not include venture capital-like or niched investment firms that only invest in life science or real estate. Since the excluded companies do not follow the same approach as the traditional CEFs of whose strategies we want to replicate, it would not be helpful to include their holdings in our sample. In addition, several of these investment firms were listed recently, and there is no evidence of the same excess returns over time as for the traditional CEFs. Lastly, we only include CEFs with over 30% listed holdings to exclude firms mainly investing in the private market.

3.2 Selection of CEF Transactions and Exclusion

To find our sample of CEF transactions, we have included each CEF's latest purchase of shares in each stock during 2010-2022. Ideally, we would have wanted to look at companies as of the date the CEFs first purchased them. Although, it is not possible due to the extraordinary long-term strategies of some CEFs. For example, Investor and Industrivärden have between 80- to 100-year holding periods in some companies. The purchase dates have been extracted from the companies' financial reports as they report their holdings and investments each quarter. We then obtained the trailing 12 months' financial ratios for the latest reported quarter since this was the latest data available when the CEFs decided to buy the stock. Since multiple CEFs have purchased some equities, they can be included several times in our sample. We do not believe this to be a bias since the CEFs have made the investment decisions independently, and the stock should be included once for each CEF. However, we only include the latest purchase per each CEF since they often increase their positions slightly several times per year. We ended up with a sample of 215 transactions for the period. Further, we have excluded target companies within Real Estate and Financials since most ratios are not comparable with the rest of the market. Lastly, we excluded targets without available data.

Our CEF sample is compared with the Swedish main list, Nasdaq OMX Stockholm. We have excluded companies traded on other lists since these are often too small to be targeted by the listed CEFs. Real Estate and Financials have been excluded to ensure comparability. Companies bought by CEFs anytime during our sample period have been excluded to separate targets from non-targets properly. See Table (2) for details and final sample sizes.

Period	**Total Companies**	**Exclusion Real Estate**	**Exclusion Financials**	**Exclusion CEF Holdings**	**Exclusion Missing Data**	**Sample after Exclusion**
Targets	215	27	36	N/A	6	**146**
Non-targets (Nasdaq OMX Stockholm):						
2022	348	39	40	72	19	**178**
2021	354	38	36	74	22	**184**
2020	330	35	33	75	13	**174**
2019	334	32	29	78	13	**182**
2018	337	30	29	83	10	**185**
2017	332	26	29	81	14	**182**
2016	312	28	29	76	10	**169**
2015	295	26	26	70	14	**159**
2014	270	24	27	62	6	**151**
2013	259	24	27	60	3	**145**
2012	261	21	25	61	5	**149**
2011	261	22	25	63	4	**147**
2010	261	19	23	61	6	**152**
2009	255	18	21	51	3	**162**
Total Obs.	**4209**	**382**	**399**	**967**	**142**	**2319**

Table 2: Exclusions in the CEF holdings sample and Nasdaq OMX Stockholm

3.3 Selection of Financial Ratios

We have qualitatively assessed the closed-end funds' strategies for its public portfolios as expressed in annual reports and company websites. This is to see if we can apply quantitative KPIs to how the closed-end funds communicate their value creation. A detailed description of the strategies can be found in Appendix (1). We have primarily used the qualitative assessment and the literature review to decide what financial ratios and other KPIs we use. The most common investment criteria among the CEFs are valuation, profitability, growth, size, financial position, and dividends. We will therefore include different measures to evaluate if the CEFs differ in these categories. Several CEFs also mention seeking quality companies and proven business models. These criteria are hard to quantify but might be included in measures such as Profit Margin and Return on Assets. Also, Fluck et al. (1997) showed that investing in low Price/Earnings and Price/Book yields higher returns for investors. Loh (1992) showed that when private equity firms do leveraged buyouts, they target companies with higher efficiency and higher debt. We will therefore add these measures to see if the CEFs have similar or other preferences. A study by Clifford (2008) shows that activist funds buy companies with lower debt levels but similar Dividend yields. Clifford mentions Jensen's FCF theory, which opens the discussion about whether the CEFs target already efficient companies or try to find room for improvement as active owners. We have therefore added Cash/Revenue to see if the targets hold a different level of cash compared with the rest of the market. Other measures mentioned in the literature review in chapter two are Revenue Growth, Analyst Coverage, and Dividend yield. We ended up with 21 KPIs that we will compare between the target and non-target groups, as seen in Table (3) below.

Valuation	**Efficiency**	**Leverage**	**Other**
P/E	ROE	Debt/Equity	Market Cap
P/B	Operating ROA	Net Debt/EBITDA	Revenue CAGR 3Y
P/S	ROIC	EBIT/Interest	Total Analyst Recommendations
EV/EBIT	EBIT Margin		Cash/Revenue
EV/EBITDA	Profit Margin		
EV/Sales	Profitable Binary		
FCF Yield			
Dividend Yield			

Table 3: Financial Ratios & KPIs

The financial ratios and KPIs have been extracted from Bloomberg (2023) and Refinitiv Eikon (2023). When possible, we have complemented missing data by hand from the company's financial statements. If not possible, the company has been excluded from the study. For example, we have excluded a limited number of companies with zero revenues since this is needed to compute several ratios. Definitions of all ratios can be found in Appendix (2).

3.4 Data Processing

We have our final sample after choosing CEFs in 3.1, finding their targets in 3.2, defining the comparable market as Nasdaq OMX Stockholm in 3.2, and choosing the financial ratios and KPIs in 3.3. However, due to significant outliers in, e.g., valuation metrics and margins, we have winsorised the data at the 95th and 5th percentiles. We have also logged the only absolute KPI in the sample, Market Cap, which we use as a proxy for company size. We have normalised all ratios in the non-target group by dividing them by the median of the Nasdaq OMX Stockholm in the same year since financial ratios change with sentiment and business cycles over time. This is done for the targets by dividing the ratios by the Nasdaq OMX Stockholm median in the same year as the transaction occurred. The normalisation implies that we look at relative values and is done since we want to compare transactions made in different periods. This means we have an unbalanced panel dataset, but we can interpret the results as a cross-sectional regression due to the normalisation.

4 Method

This chapter will describe our methodological approach to answer our research question and test our hypotheses statistically.

4.1 Univariate Examination

The first step of our study is to answer whether we have significant differences between the target and non-target groups. We will do a univariate examination similar to Loh (1992), who studied the characteristics of buyout targets. A two-tailed t-test will be used to determine if there are significant differences between the groups. First, we will conduct an f-test to examine whether the groups have equal variances. This determines whether to run the t-test with homoscedastic or heteroscedastic variances. The results will allow us to analyse and draw conclusions about our hypotheses concerning differences between the groups and are used in the model selection to decide which factors to include in the logistic regression. The significantly different KPIs will be considered to be included in the logistic regression, where higher significance increases the probability for the KPI to be included. However, to avoid multicollinearity, we will not include all significant KPIs from the same category, such as P/E and EV/EBIT.

4.2 Logistic Regression

The second step is to decide which companies in the investable universe fit the characteristics we find in the CEF target group. We will pick significantly different predictors in the univariate examination to predict targets. We then run a cross-sectional multivariate logistic regression with a dummy as the dependent variable representing targets and non-targets. A logistic regression model is suitable since we have a classification problem with a binary qualitative response variable, i.e., 0 or 1. James et al. (2017) describe that the output will be the probability of the firm belonging to the target group. Using a linear regression model would not make sense since we want to obtain probabilities between 0 and 1. A general multivariate logistic function is presented below in Formula (1), which is the probability of the dependent variable taking the value one given the explanatory variables.

$$P(D_i = 1|x_i) = \frac{e^{\beta_0+\beta_1 X_1+\cdots+\beta_p X_p}}{1 + e^{\beta_0+\beta_1 X_1+\cdots+\beta_p X_p}}$$

Formula (1): Logistic function

The nominator is the natural exponential function of a multivariate linear function, and the denominator is one plus the same natural exponential function. To obtain the estimates, we use maximum likelihood to fit the model. This function will create an S-shaped curve, see Figure (3) with outputs between 0 and 1.

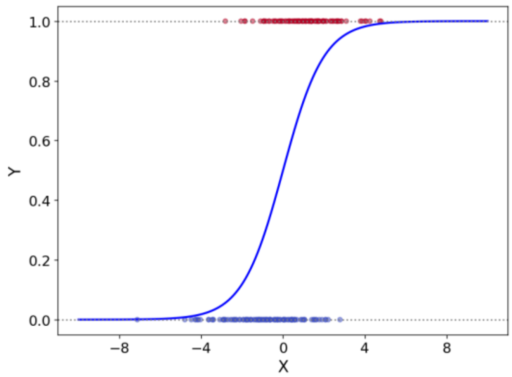

Figure (3): Example of the logistic s-shaped curve with random datapoints

The logistic function will always produce a reasonable prediction regardless of what values we obtain in our predictors. James et al. (2017) describe how maximum likelihood will produce estimates of betas, yielding an output from the logistic function close to one for those classified as targets and otherwise close to zero. The maximum likelihood optimisation will be done through Python, and the technical details are beyond the scope of this thesis. The dataset will be split into one training and one test sample, allowing us to test the accuracy of the model's predictions. The split will be 90%, respectively 10% for the training and test sample. The model will be evaluated using a confusion matrix, and the model selection will be based on accuracy. Econometric robustness will be presented in Appendix (3), describing how multicollinearity was managed to arrive at the final model specification.

4.3 Synthetic CEF Portfolio

The third step in our study is to use the beta estimates from the logistic regression to make predictions deciding which firms hypothetically would be a typical target according to our model. We apply the model to the Nasdaq OMX Stockholm to build portfolios, excluding the firms already targeted by CEFs. The exclusion is made since a historical replication of CEFs could be done by buying the same firms CEFs have had in their portfolios. The goal is instead to find what characteristics represent a typical CEF target. The function displayed in Formula (1) will be applied using our beta estimates obtained by the maximum likelihood optimisation in the logistic regression.

CEFs have, on average, 7-8 stocks in the public equity portfolio. However, only including 7-8 stocks in our synthetic portfolios would give us a risk profile much higher than the CEFs' actual portfolios since they, in addition, diversify by a similar number of investments in private companies. Buyouts and de-listings are other reasons for including more than 7-8 stocks at the start since we otherwise would end up with too few companies. In comparison, Statman (1987) describes that a well-diversified portfolio consists of at least 30 equities. The goal is not to have a well-diversified portfolio but rather a focused portfolio similar to what CEFs typically hold. CEFs have a total of 15 equities on average, both public and private, and therefore we argue that 15 equally weighted equities are a suitable choice.

The CEFs probably, to some extent, balance their portfolios by adding more to small positions or selling small parts of their winners. However, we observe that Creades has over 30% of their portfolio in Avanza, Kinnevik has 25% in Tele2, Latour has 20% in Assa Abloy, Spiltan has almost 50% in Paradox, Öresund has 27% in Bilia, Lundbergs has around 20% respectively in Holmen, Industrivärden, and Indutrade, and Bure Equity has 35% in Mycronic and 28% in Vitrolife. Therefore, we assess that the CEFs are not afraid to let their winners run to make up a large part of the portfolio, which is why we do not rebalance the portfolios over the holding period. However, the concentrated portfolios are often a result of the performance over time which is why we start with equally weighted portfolios. We could implement numerous portfolio strategies but want to replicate the CEFs to the greatest extent possible. In addition, we want to make the replication as simple as possible and therefore argue that equally weighting 15 equities without rebalancing is suitable. However, robustness tests will be conducted to test if the results are stable and not dependent on a specific portfolio size.

The strategy is to form portfolios by including the 15 equities with the highest values from the logistic regression and classify those as hypothetical targets. This will be done each year with a minimum holding period of 5 years starting in 2010 until 2022-12-31 to capture different investment horizons and adjust for potential bias related to the time period. This is an appropriate choice since CEFs generally have a long-term strategy according to our qualitative assessment, seen in Appendix (1). Furthermore, if a company is de-listed from the stock exchange, we will distribute the cash evenly between the remaining equities. The back-test of the portfolios should be considered semi-out-of-sample since the logit model is not trained on stock return data but instead on financial characteristics at a specific point in time. Also, the actual CEF targets are excluded from the Nasdaq OMX Stockholm, which means our portfolios will contain entirely new companies. This should instead be considered a downward bias for our portfolios since we exclude many good investments from the universe. However, a clean out-of-sample evaluation will be conducted in the US market by applying the same model to the S&P 500. We will also start five years earlier to test the model out-of-sample regarding the holding period and market environment.

4.4 Portfolio Performance

The last step of our study is to evaluate the portfolio performance by Excess Cumulative Return and Excess Compounded Annual Growth Rate (CAGR). Excess return is defined as the return above the market indices OMXSGI and S&P 500. We will use Standard Deviation and Maximum Drawdown to measure risk and Sharpe Ratio to measure the risk-adjusted return. We will also evaluate the performance with Jensen's Alpha using the Fama and French (1993) three-factor model, which found company size and value in book-to-market to explain returns above the market. Jensen's alpha is the excess return not captured by the factors (Jensen, 1967). The measure is commonly used to evaluate portfolio performance. The factors for the US and the European market, where Sweden is included, have been obtained from French's (2023) data library.

5 Empirical Findings

This chapter will present the empirical findings of the thesis, starting with the univariate comparison between targets and non-targets. We will then show the composition of the synthetic portfolios and their performance.

5.1 Univariate Evaluation

The results from the univariate examination between the two groups, targets and non-targets, are presented in Table (4) below. We show the average of the groups' normalised numbers and the difference together with the significance level of the t-test results.

KPI	Target Average	Non-targets Average	Difference
P/E	1.1	1.3	-0.2 *
P/B	1.4	1.4	0.0
P/S	1.7	4.6	-2.9 ***
EV/EBIT	0.6	1.2	-0.7 **
EV/EBITDA	1.1	1.3	-0.2
EV/SALES	1.8	3.7	-2.0 ***
FCF Yield	1.2	0.5	0.7 ***
Dividend yield	2.4	1.6	0.9 ***
ROE	1.1	0.5	0.6 ***
Operating ROA	1.1	0.6	0.5 ***
ROIC	0.9	0.8	0.1
EBIT Margin	0.6	-4.5	5.1 ***
Profit Margin	15.5	-6.6	22.1 ***
Profitable (binary)	0.9	0.8	0.1 ***
Debt/Equity	1.5	1.5	0.0
Net Debt/EBITDA	1.8	1.3	0.5
EBIT/Int. Expense	1.7	-0.6	2.3 ***
Market Cap	3.8	6.3	-2.5 ***
Revenue CAGR 3Y	3.6	2.1	1.4 **
Analyst Rec.	3.7	2.5	1.1 **
Cash/Revenue	2.8	6.3	-3.5 ***

Table (4): Univariate KPI comparison with the following significance levels: 10%=*, 5=**, 1%=***

Valuation measures such as Price/Sales, EV/EBIT, FCF yield, and EV/Sales are significantly different between the groups. Targets have an average Price/Sales of 1.7x and the non-targets 4.6x, and we can conclude by the simple univariate examination that CEFs typically buy cheaper firms. The same pattern can be found in EV/EBIT and EV/Sales, where targets are trading at lower multiples. The target group has a higher Dividend yield, which signals a lower price paid for the cash flow distributed to shareholders. Return on Equity and Operating Return on Assets are higher for targets. Hence, more efficient companies are more likely to be classified as targets. We can also observe that targets are more profitable with better EBIT and Profit margins. The leverage measures Debt/Equity and Net Debt/EBITDA are not significant, while the interest coverage ratio in EBIT/Interest Expense is significant. Target companies have a higher ability to cover their interest payments than the non-targets but are not levered to a greater extent. Market Cap and 3-year Revenue CAGR significantly differ and signal that

CEF targets are smaller firms with higher historical revenue growth. Analyst coverage is higher for the targets, and Cash/Revenues provide evidence that targets hold less excess cash.

5.2 Logistic Regression and Synthetic Portfolio Construction

Based on the results of the univariate examination, a selection of explanatory variables has been conducted by picking measures with significant differences between the groups. Our starting point has been to choose significant variables which should have limited multicollinearity. Therefore, we only included one valuation, profitability, and efficiency measure, et cetera. We have used this approach and been relatively restrictive with running specification tests to limit the number of type 1 and 2 errors. Of the valuation measures, we chose Price/Sales as it was the most significant ratio. In addition, EV/EBIT and Price/Earnings can be negative, which might cause our model to pick companies with large negative ratios, which is undesirable. Operating ROA and EBIT margin have been selected in their respective categories since more data points are available for these ratios than the alternatives. Also, ROA is the most widely used ratio in previous research (Aslan & Kumar, 2016; Brav et al., 2008; Carrothers, 2017; Clifford, 2008). Another reason for choosing EBIT margin over Profit margin is that the Binary Profitable measure is based on the Profit margin. However, we excluded EBIT/Interest Expense, Total Analyst Recommendations and Cash/Revenues due to high correlation with other explanatory variables. The logit model is specified in Formula (2) below.

$$P(D_i = 1|x_i) = \frac{e^{\beta_0+\beta_1 P/S+\beta_2 Div\,Y+\beta_3\,Op\,ROA+\beta_4\,EBIT\%+\beta_5\,Profitable+\beta_6\,Market\,Cap+\beta_6\,Revenue\,CAGR\,3Y}}{(1+e^{\beta_0+\beta_1 P/S+\beta_2 Div\,Y+\beta_3\,Op\,ROA+\beta_4\,EBIT\%+\beta_5\,Profitable+\beta_6\,Market\,Cap+\beta_6\,Revenue\,CAGR\,3Y})}$$

Formula (2): Logit Model

The dataset has been split into a training sample of 90% of the complete dataset. The remaining 10% will be used as a test sample, allowing us to evaluate and test the model's predictive power. The regression results are displayed in Table (5) and are run with robust standard errors, known as HC3. The number of observations was 2227 with a Pseudo R-Square of 0.052.

	Coefficient	Standard Error	P-Value
Constant	-3.082 ***	0.237	0.000
Price-to-Sales	-0.084 *	0.039	0.031
12M Dividend Yield	0.151 ***	0.035	0.000
Operating ROA	0.027	0.042	0.516
EBIT Margin	-0.002	0.009	0.807
Profitable Binary	0.174	0.295	0.557
Market Cap	-0.007 *	0.003	0.022
Revenue CAGR 3Y	0.041 **	0.015	0.006

Table (5): Logit model regression results with the following significance levels: 10%=*, 5=**, 1%=***

Similar to the univariate examination and based on Table (5), we can conclude that the logit model will pick companies with a low valuation but high Dividend yield and Operating ROA. The coefficient for the EBIT margin is negative but close to zero and will therefore have an immaterial impact on the model. Profitable companies are more likely classified as targets, and a negative coefficient for Market Cap implies that smaller companies are more likely to be picked. High growth will have the same impact with a positive coefficient for the 3Y Revenue CAGR.

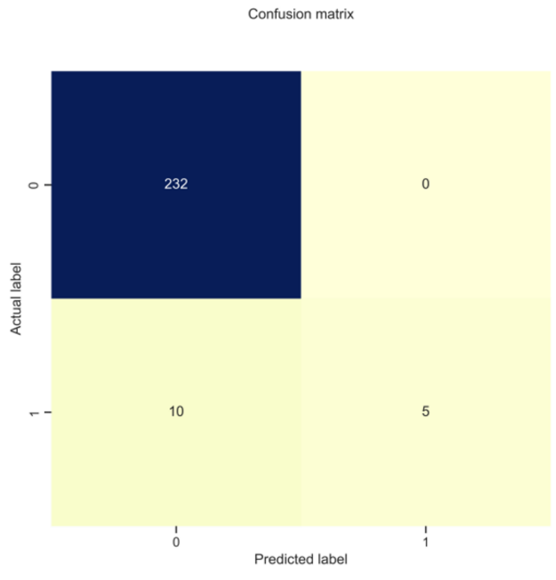

Figure (4): Confusion Matrix

We have constructed a confusion matrix to evaluate the model's predictive power, which was used to select the model with the highest accuracy. We can observe that the final logit model classifies 33% of the targets and 100% of the non-targets to the correct group based on the results displayed in Figure (4).

5.3 Portfolio Composition

The logit model has been implemented on the Swedish equity market to pick 15 equities each year 2010-2018 with the best fit, i.e., the highest values in the logistic function and form portfolios. Descriptive statistics and a comparison against the market from the start date until 2022-12-31 can be found in Table (6).

	Median		Median		Median		Median		Average		Median		Median	
Start Year	**Price-to-sales**		**12M Dividend Yield**		**Operating ROA**		**EBIT Margin**		**Profitable binary**		**Market Cap (MSEK)**		**Revenue CAGR 3Y**	
	Portfolio	**OMXS GI**	**Portfolio**	**OMXS GI**	**Portfolio**	**OMXS GI**	**Portfolio**	**OMXS GI**	**Portfolio**	**OMXS GI**	**Portfolio**	**OMXS GI**	**Portfolio**	**OMXS GI**
2010	0,26	0,49	6,0%	1,2%	6,6%	4,8%	5,9%	5,9%	100%	72%	416	937	8,6%	9,0%
2011	0,59	0,86	5,3%	0,7%	10,2%	5,5%	9,5%	4,2%	93%	68%	323	1065	10,7%	3,4%
2012	0,75	1,02	4,0%	1,9%	9,5%	7,6%	6,3%	6,0%	93%	75%	310	1012	20,4%	1,0%
2013	0,53	0,77	8,9%	2,3%	7,1%	7,2%	7,7%	6,3%	73%	74%	499	859	8,2%	6,1%
2014	0,60	0,83	4,8%	1,7%	8,4%	6,0%	6,0%	6,2%	93%	73%	706	1157	10,4%	4,6%
2015	0,79	1,10	2,3%	1,3%	10,0%	7,1%	8,2%	6,0%	87%	72%	555	1385	59,1%	1,9%
2016	0,49	1,09	5,8%	1,3%	12,7%	8,0%	7,2%	7,2%	100%	76%	543	2087	4,5%	3,7%
2017	0,69	1,24	5,3%	1,4%	11,5%	7,5%	6,9%	6,8%	100%	79%	912	2747	4,8%	7,0%
2018	0,71	1,27	6,0%	1,5%	8,9%	7,7%	7,6%	7,4%	100%	79%	864	2902	6,2%	7,2%
Average	**0,60**	**0,96**	**5,4%**	**1,5%**	**9,4%**	**6,8%**	**7,2%**	**6,2%**	**93%**	**74%**	**570**	**1 572**	**14,8%**	**4,9%**

Table (6): Descriptive Statistics for the Swedish Portfolios running from the start date to 2022-12-31

Similar to the actual targets, the model has picked firms with lower valuations regarding Price/Sales. Dividend Yield and profitability are higher, and the operational efficiency in terms of Operating ROA is better than the average on OMXSGI, which is consistent with the actual CEF targets. The model picks more profitable companies of smaller size with higher growth in terms of 3Y Revenue CAGR. These results confirm that we have managed to build a model that captures the CEF targets' financial characteristics. The portfolio sector composition is displayed in Figure (5), and we can observe an overweight to Industrials, Information Technology and Consumer Discretionary, representing 74% of the total portfolio.

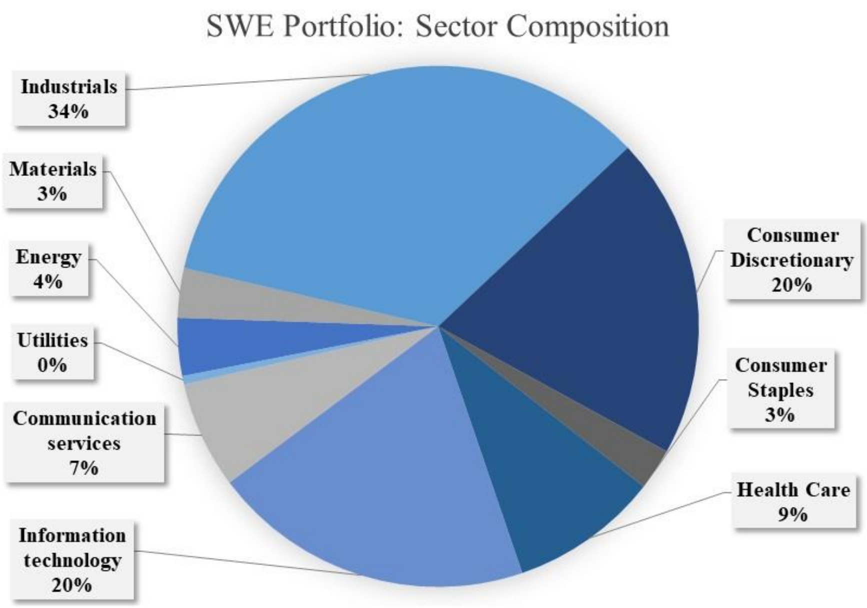

Figure (5): Sweden Portfolio Sector Composition

5.4 Performance of the Synthetic CEF Portfolios

Table (7) below presents the performance of the synthetic portfolios. Since we want to capture the CEF's long-term strategies, we evaluate the performance of portfolios with at least five-year holding periods, making 2010-2022 the first holding period and 2018-2022 the last. As seen in the table, our strategy has a positive cumulative return above the market in six out of nine portfolios with an average of 216% and a CAGR above the market of 7% on average. We can observe an asymmetry with limited downside risk regarding the excess cumulative return. For example, the worst-performing portfolio is only 32% behind the market, while the best-performing year is almost 800% ahead of the market. Five portfolios have significant Jensen's Alphas, with regression outputs found in Appendix (5). Not surprisingly, since the portfolios are relatively concentrated, the risk measures, Standard Deviation and Maximum Drawdown, are higher for our portfolios than for the market. Although, the Sharpe ratio is higher on average for the synthetic portfolios, indicating that higher returns compensate for the additional risk.

Start Year	Excess Cum. Ret.	Excess CAGR	Jensen's Alpha		Standard Deviation		Max Drawdown		Sharpe ratio	
		Portfolio			Portfolio	OMXS GI	Portfolio	OMXS GI	Portfolio	OMXS GI
2010	221%	4%	0.7%	*	23%	16%	-34%	-30%	0.68	0.68
2011	-14%	0%	0.4%		22%	16%	-32%	-30%	0.49	0.62
2012	796%	12%	1.6%	**	31%	16%	-47%	-30%	0.85	0.78
2013	-27%	-1%	0.4%		22%	16%	-39%	-30%	0.55	0.75
2014	199%	8%	1.1%	**	24%	16%	-31%	-30%	0.79	0.65
2015	330%	15%	1.5%	**	29%	17%	-42%	-30%	0.86	0.61
2016	350%	18%	1.8%	**	30%	17%	-29%	-30%	0.95	0.61
2017	119%	10%	1.2%		29%	18%	-35%	-30%	0.75	0.59
2018	-32%	-5%	0.5%		28%	19%	-33%	-30%	0.29	0.56
Average	**216%**	**7%**	**1.0%**		**26%**	**17%**	**-36%**	**-30%**	**0.69**	**0.65**

Table (7): Sweden Synthetic CEF 15 Equities Portfolio & Index Performance with the following significance levels: 10%=*, 5=**, 1%=***

We have also tested the robustness of the performance in the Swedish market by checking for sensibility concerning portfolio size. First, we include ten equities instead of the previous 15. The results are displayed in Table (8) below, showing significant overperformance and stable results compared to the strategy including 15 equities. An investor applying the strategy with ten companies would, on average, receive a 2% extra annual return with a similar risk profile compared to the portfolio of 15 companies during the sample period.

Start Year	Excess Cum. Ret.	Excess CAGR	Jensen's Alpha		Standard Deviation		Max Drawdown		Sharpe ratio	
		Portfolio			Portfolio	OMXS GI	Portfolio	OMXS GI	Portfolio	OMXS GI
2010	540%	8%	0.6%	*	28%	16%	-33%	-30%	0.71	0.68
2011	31%	1%	0.4%		21%	16%	-32%	-30%	0.54	0.62
2012	1137%	15%	1.6%	**	23%	16%	-26%	-30%	1.17	0.78
2013	-54%	-2%	0.3%		25%	16%	-49%	-30%	0.48	0.75
2014	151%	6%	1.1%	**	23%	16%	-35%	-30%	0.75	0.65
2015	457%	18%	1.5%	**	31%	17%	-40%	-30%	0.90	0.61
2016	444%	20%	1.8%	**	33%	17%	-30%	-30%	0.94	0.61
2017	247%	17%	1.2%		30%	18%	-28%	-30%	0.94	0.59
2018	-33%	-5%	0.5%		29%	19%	-39%	-30%	0.29	0.56
Average	**324%**	**9%**	**1.0%**		**27%**	**17%**	**-35%**	**-30%**	**0.75**	**0.65**

Table (8): Robustness test: 10 equities with the following significance levels: 10%=*, 5=**, 1%=***

We observe similar results in Table (9) below when increasing the number of equities to 20. As expected, the risk is decreased by adding companies to the portfolio. However, the risk-adjusted return increases as the returns remain substantially above the market. Most importantly, the robustness test shows that the portfolio size is not decisive of whether our strategy beats the market.

Start Year	Excess Cum. Ret.	Excess CAGR	Jensen's Alpha		Standard Deviation		Max Drawdown		Sharpe ratio	
		Portfolio			Portfolio	OMXS GI	Portfolio	OMXS GI	Portfolio	OMXS GI
2010	288%	5%	1.0%	*	22%	16%	-31%	-30%	0.73	0.68
2011	-28%	-1%	0.4%		18%	16%	-27%	-30%	0.53	0.62
2012	1735%	19%	0.5%	**	26%	16%	-35%	-30%	1.18	0.78
2013	26%	1%	0.3%		21%	16%	-35%	-30%	0.65	0.75
2014	168%	7%	1.1%	**	21%	16%	-27%	-30%	0.82	0.65
2015	283%	13%	0.5%	*	24%	17%	-24%	-30%	0.94	0.61
2016	266%	14%	2.1%	**	26%	17%	-28%	-30%	0.94	0.61
2017	81%	7%	1.8%	**	24%	18%	-30%	-30%	0.76	0.59
2018	-31%	-5%	0.6%		25%	19%	-35%	-30%	0.31	0.56
Average	**310%**	**7%**	**0.9%**		**23%**	**17%**	**-30%**	**-30%**	**0.76**	**0.65**

Table (9): Robustness test: 20 equities with the following significance levels: 10%=*, 5=**, 1%=***

5.5 Out-of-Sample Performance

Testing the model out-of-sample in the US market using S&P 500 resulted in the following portfolio composition, which can be seen in Figure (6). We can observe an overweight to Communication Services, Energy and Utilities, representing 51% of the total portfolio. Energy and Utilities comprise 30%, compared to only 4% in the Swedish portfolio. This is while Consumer Discretionary, Industrials and Information Technology only make up 25% compared to the 74% in the Swedish portfolio.

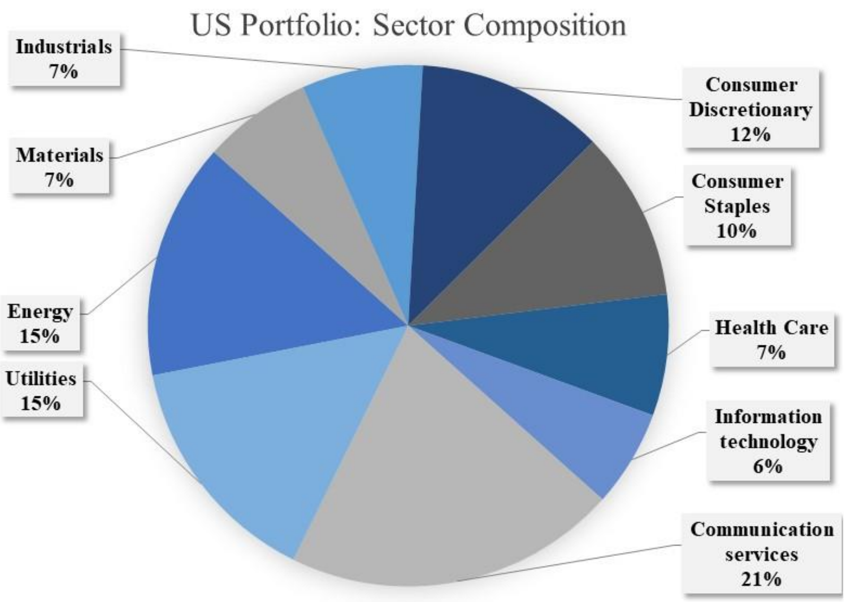

Figure (6): US Portfolio Sector Composition

As seen in Table (10), the out-of-sample performance is weak, with a consistent underperformance compared to the market. The regression output can be found in Appendix (6). We can also observe higher risk regarding Standard Deviation and Maximum Drawdown, resulting in a lower Sharpe Ratio.

Start Year	Excess Cum. Ret.	Excess CAGR	Jensen's Alpha	Standard Deviation		Max Drawdown		Sharpe ratio	
		Portfolio		Portfolio	S&P 500	Portfolio	S&P 500	Portfolio	S&P 500
2005	134%	2%	0,2%	17%	15%	-50%	-51%	0,50	0,45
2006	-48%	-1%	0,0%	17%	16%	-48%	-51%	0,39	0,46
2007	-74%	-1%	-0,1%	18%	16%	-48%	-51%	0,34	0,44
2008	-85%	-1%	0,0%	17%	16%	-47%	-46%	0,34	0,45
2009	-75%	-1%	0,0%	21%	15%	-43%	-24%	0,54	0,73
2010	-58%	0%	0,1%	18%	15%	-29%	-24%	0,55	0,70
2011	-40%	-1%	0,1%	15%	15%	-19%	-24%	0,64	0,70
2012	-79%	-2%	-0,3%	19%	14%	-32%	-24%	0,51	0,77
2013	-136%	-6%	-0,4% *	16%	15%	-24%	-24%	0,35	0,73
2014	-119%	-8%	-0,3%	18%	15%	-32%	-24%	0,12	0,60
2015	-46%	-3%	-0,2%	19%	16%	-25%	-24%	0,34	0,56
2016	-29%	-2%	-0,2%	22%	16%	-35%	-24%	0,42	0,62
2017	-12%	-1%	0,0%	18%	17%	-28%	-24%	0,51	0,59
2018	-20%	-3%	-0,2%	23%	19%	-35%	-24%	0,30	0,47
Average	**-49%**	**-2%**	**-0,1%**	**18%**	**16%**	**-35%**	**-31%**	**0,42**	**0,59**

Table (10): US Synthetic CEF Portfolio & Index Performance with the following significance levels: 10%=*, 5=**, 1%=***

6 Analysis

In this chapter, we aim to answer and analyse the overarching research question:

> What firm characteristics represent a typical CEF target in the public equity market, and can we use these characteristics to build a synthetic equity portfolio and outperform the market?

We will analyse the univariate tests and regression coefficients to answer the two first hypotheses, i.e., regarding differences between the target and non-target groups. After that, we will discuss hypothesis three by analysing the performance of our synthetic portfolios.

Our t-tests and logit regression results show that CEFs, on average, target lower-valued companies. This is in line with several CEFs' own definitions of their strategies. For example, Creades, Traction, Öresund, and Byggmästare AJ Ahlström mention valuation as a key criterion when investing. This might also explain why the CEFs have outperformed the market since previous research (Fluck et al., 1997 and Lewellen, 2004) has shown that strategies buying lower-valued stocks beat the market. The research field of activist investors (Clifford, 2008; Brav et al., 2008; Carrothers, 2017; Aslan & Kumar, 2016) shows unanimous results of target companies having lower than average valuations, i.e., in line with the results we show of CEFs. This implies that activist investors have a view which differs from the market regarding future opportunities. For example, Greenwood and Schor (2009) describe that activists target companies with poor-performing stocks which could also be a reason for the lower valuations. Hence, CEFs may also target companies with poor-performing stocks that the market does not favour. Since the CEFs do not face the same risk as mutual funds regarding short-term focused investors and capital outflows, they can afford to take long-term bets and purchase companies that the market currently does not appreciate.

The discussion above implies that the target company is somewhat neglected or disapproved by the market since other characteristics, like profitability and operational efficiency, imply better-than-market quality. It is hard to point out why, but for some reason, the CEFs find value where others do not. Fredrik Lundberg, the CEO of Lundbergsföretagen, might have a good explanation; "The reasons behind choosing companies should be moderately rational, i.e., it is also important to invest with its senses" (Lundbergsföretagen, 2023b, p.7). The senses, i.e., experience, knowledge, and the instincts of historical leaders like Lundberg or the recently deceased Gustaf Douglas, founder of Latour, cannot be replicated by a quantitative study. Another example of a critical investment criterion that has been hard to incorporate in the study is that many of the CEFs value an excellent management team highly. Other examples are the potential for geographical expansion, good brands, and market outlook. Many of the CEFs are also discussing sustainability as an essential factor. Since our study is constructed with a high dependency on historical data, a sustainability factor would have been challenging to incorporate.

Our study further shows that the CEFs invest in profitable companies with higher-than-market margins and efficiency. These findings were expected since our qualitative assessment of the strategies showed that most CEFs mention profitability, quality, or proven business model as key investment criteria. Previous research (Aslan & Kumar, 2016; Brav et al., 2008; Carrothers, 2017; Clifford, 2008) shows activist investors also target companies with high ROA. This might indicate that activist investors, as well as the CEFs, not only target bad-performing companies but instead focuses on making already well-run companies even better.

Several CEFs express strategies to target companies with high Dividend yields, e.g., Öresund and Svolder. Our results confirm this and may explain some overperformance, supported by Lewellen (2004), who showed that investing in high Dividend yields receives excess returns. Maupin et al. (1984) showed that private equity buyout targets have a higher Dividend yield, while Clifford (2008) showed that the Payout Ratio of activist investors' targets is not different from the average. We believe that the high Dividend Yield, Operating ROA, and less excess cash provide evidence that the CEFs target already efficient and well-run companies rather than trying to find investments with room for improvement. This is confirmed by the positive coefficients in the logit model for Dividend yield and Operating ROA.

However, we cannot exclude the possibility of active ownership to explain the outperformance in combination with the fact that the CEFs target good companies. For example, Clifford (2008) showed that activist investors can increase their targets' ROA despite purchasing higher-than-average-performing businesses. While we do not doubt the CEF's ability to create value as active owners, we still conclude that the investment approach differs from pure activist hedge funds, which are often targeting low growth (Aslan & Kumar, 2016; Boyson & Mooradian, 2011), and according to some research contradicting Clifford (2008), worse than industry performance (Greenwood & Schor, 2009). This since we provide evidence that the CEFs buy better-performing companies.

Other measures with significant differences between the groups are Size, Revenue Growth, and Analyst Coverage. This can also be observed in the regression coefficients having a positive beta for Revenue CAGR and a negative for Market Cap. Our results show that CEFs target companies smaller than the average stock listed on Nasdaq OMX Stockholm. This is probably because we have included all listed CEFs in our study. Not all firms have the capital, such as Investor, Latour or Industrivärden, to own a significant stake in large-cap companies. The qualitative assessment of the companies shows that many of the CEFs want to own a substantial part of their holdings to have influential ownership. However, Svolder focuses on small and medium companies since they are often overlooked (Svolder, 2023b) and therefore expected to yield higher returns. The fact that a higher number of analysts cover the CEF holdings than the average listed company indicates that they are not overlooked on average. Although, it is hard to generalise all our results as the CEFs have differences between themselves as well. When it comes to growth, it is clearly a driver for, e.g., Kinnevik, Öresund and Spiltan, while other CEFs are more valuation- or quality-driven. Although, as a group, the CEFs invest in faster-growing companies. Fluck et al. (1997) could not show that investing in faster-growing stocks performed better in the US market. The growth is another difference between activist hedge funds and the CEFs, as both Boyson and Mooradian (2011) and Aslan and Kumar (2016) showed that activists target slower-growing companies. Again, this implies that the CEFs, to a more considerable extent, focus on already well-run companies compared with pure activist investors.

Neither Net Debt/EBITDA nor Debt/Equity showed to be significantly different between the targets and non-targets. This is surprising since many CEFs mention financial position or low risk as key investment criteria. A potential explanation may be the significant ownership and generally low leverage within the CEFs, enabling them to add additional capital if needed. This reduces the refinancing risk and hence the relevance of the leverage measures. The results are also not in-line with Loh (1992), who showed that private equity firms target companies with high debt levels in LBOs, further proving that the CEFs have their own investment strategy compared to other investor groups.

After analysing the univariate examination and the logit model coefficients, we reject hypotheses $H0_1$ and $H0_2$ since we have shown significant differences between the targets and non-targets. We have also demonstrated that the CEFs target well-managed companies with good operating performance instead of low-performing companies with much room for improvement. We have shown that the CEFs target companies with lower valuation, higher profitability, higher efficiency, higher growth, and higher interest coverage ratio. Is it that simple to beat the market with a long-term approach, and can we replicate it?

The historical performance of the synthetic CEF portfolios indicates that we have managed to create a successful strategy which has the potential to outperform the Swedish stock market significantly. Hence, we reject $H0_3$ since we managed to produce excess returns by constructing portfolios with specific firm characteristics similar to those CEFs holdings have at purchase. We can observe that 67% of the portfolios outperform the market by a factor larger than 1x, and 56% have a significant alpha, see Table (7). These results are further strengthened since we find an increased performance by changing the number of equities and still beating the market, as seen in Tables (8) and (9). It would benefit a less risk-averse investor to choose the strategy including ten equities, decreasing the diversification. Twenty equities would be preferable for an investor with higher risk aversion since the Standard Deviation and Maximum Drawdown are lower. Still, returns are higher than the portfolio including 15 stocks. Nevertheless, the results point in the same direction, proving that our model can find high-performing companies in the Swedish equity market, independent of portfolio size.

The results of the portfolios contradict Kendall's (1953) and Fama's (1970) research covering the randomness of stock price movements and the efficient market hypothesis, stating that all information will be immediately incorporated into the stock price. Instead, our results indicate that financial ratios can be a sufficient tool to predict future stock returns and used to construct portfolios beating the market. Our results provide evidence for two arguments. First, CEFs target companies with specific characteristics, and second, firms covered by these characteristics have the potential to outperform the market. The second argument is strengthened by Ou and Penman (1989) and Fluck et al. (1997), who suggested that financial ratios have a predictive power of future stock returns. We argue that the CEF's strategy has a high ability to pick high-performing equities, which our study confirms since we managed to outperform the market significantly with a majority of the portfolios.

Malkiel (2003) suggested that fund managers are not able to overperform the stock market, which implies that the predictability of stock returns is limited. Our study shows that a patient investor with a long investment horizon is required to form portfolios and beat the market with our model, which can be seen in Appendix (4). Several of the portfolios perform in line with the market for years before they separate and instead overperform. Malkiel (2003) concluded that actively managed funds underperform comparable stock indices. Contrary to mutual funds, CEFs can have a longer investment horizon by not having to keep excess liquidity to service fund withdrawals from investors. CEFs are more like hedge funds described by Clifford (2008), suggesting that more extended lockup of investor capital creates a better ability to have a long-term investment horizon. Additionally, it also increases the probability of participating in investor activism. If active ownership plays a significant role in value creation, which Clifford's study has shown, this might have a material impact. Hence, we buy companies with the financial characteristics to be a CEF target. Still, the potential upside from active ownership in those firms is never utilised, as the real targets are excluded.

Another important aspect is the investment risk. Unsurprisingly, since the portfolios are concentrated, our results indicate that the risk of the synthetic CEF portfolios regarding Standard Deviation and Maximum Drawdown is higher. OMXSGI is constituted by all stocks on the Nasdaq OMX Stockholm, which will undeniably be less affected by movements in individual stocks compared to a relatively small portfolio with only 15 equities. Hence, the risk will be higher, but this is not symmetric to the returns as an increase of six percentage points in Maximum Drawdown and nine percentage points higher standard deviation gives the investor access to an excess CAGR of 7% above the market. The Sharpe Ratio is also higher on average for our portfolios. Our findings also show that it is enough to pick up a few high-performing equities, and those will not only compensate for equities that completely collapse but also create significant returns for the portfolio. This emphasises the asymmetry of equity returns with an infinite upside but a limited downside. This is seen in Table (7) with a minimum Excess Cumulative Return of -32%, while the maximum reaches almost 800%.

The Swedish portfolios' sector composition should be considered diversified as we do not have excessive exposure against only one individual sector which has been outperforming the market over the sample period. Hence, we limit potential bias from having a model that picks firms from a particular sector that generally outperformed the market. We can also observe that the sector representation is similar to what CEFs state in their strategies, with Industrivärden, Investor and Latour favouring Industrials. CEFs also focus on strong branding and reputation, which is particularly important for Consumer Discretionary, in which our portfolios have 20% exposure. We also know from the qualitative assessment that Spiltan and Kinnevik strongly focus on Information Technology which amounts to 20% of our synthetic portfolios. Therefore, we argue that our model creates portfolios comparable to our CEF sample regarding sector representation.

However, moving focus to our out-of-sample study, our model picked very different companies in the US market. The model suggested investments with overweight in Utilities and Energy instead of Industrials and Information Technology, which the CEFs historically have owned. This can partly be explained by not incorporating a sustainability measure in the logit model, which would probably have excluded many selected Energy and Utility companies. Concerning sector representation, we can conclude that the model did not create a probable CEF portfolio out-of-sample. This can also be seen in the performance of the portfolios, as only one of the 14 portfolios managed to beat the market, while all portfolios also had a higher risk. Therefore, we argue that our strategy works best in the Swedish market, where the model was trained. The reason is that the Swedish market and the index composition look different from many other markets with, for example, a large part export-heavy industrials. In addition, the S&P 500 was hard to outperform over the last decade if your model does not pick any global tech companies which have had a superb performance and make up a large part of the index. We have found that a model trained on specific company characteristics cannot always be transferable to a different market. However, remember that the Swedish portfolios excluded all companies purchased by a CEF anytime during our sample. We thereby beat the OMXSGI even if we excluded all historical CEF holdings in the sample period independent of the year of investment from our investible universe. Judging by the CEF's general performance over the last decade, it would have been easier to beat the market by not excluding their historical holdings. Therefore, we argue that the model is sufficient to beat the market, given that it is trained and implemented in the same market. It could be argued that our results have limited generalisability since we only tested the model over a specific period. However, as mentioned in the introduction, CEFs have historically outperformed the market over at least 20 years. Hence, we argue that our replicating CEF strategy would show similar results if tested in a different period on the Swedish market.

7 Conclusion

The research field within target prediction and using company characteristics to predict stock returns is extensive. However, the research on closed-end funds is not well covered. This thesis presents evidence that CEFs distinguish themselves from the rest of the market by investing in companies with specific financial characteristics in terms of lower valuation but higher profitability, efficiency, growth, number of analyst recommendations, and interest coverage ratio. At the same time, we cannot find differences in leverage. The results further imply that the CEFs target well-managed companies with good operating performance instead of low-performing companies with much room for improvement. The study also shows that it is possible to build a synthetic CEF portfolio from these characteristics and outperform the market to a relatively high degree with a passive buy-and-hold strategy. This is given that the model is trained on characteristics implemented by the leader in the particular market where the model picks companies since we observe weak performance in the US.

Furthermore, we have managed to create a strategy which has usability for a retail investor since all information origins from public market data. However, the method requires extensive data processing and is time-consuming, limiting its practical usability. Moreover, CEFs invest in lower-valued companies with high operational performance. Therefore, a study covering the development in operating performance when a CEF enters as a shareholder would be highly relevant, similar to Clifford's (2008) study of hedge funds. This is to study further the CEFs' ability to create value by active ownership. In addition, it would be interesting to study the stock price reaction when CEFs enter a company to understand how the market values CEFs as owners.

A limitation in our ambition to shed light on the value creation in CEFs is that we only look at the public holdings. It would be possible to broaden our study and include private equities for further research. Specifically since the interest in the CEFs' private holdings has increased recently. For example, Kvartil (2023) has launched a fund that invests in the Swedish CEFs and then neutralises the public equities by short positions to be purely exposed to private holdings. A similar approach could have been conducted to further research the private investments' impact. However, the study would lose the possibility of building replicating portfolios since most private equities are not available for retail investors. Another interesting twist to our research would be to pick the best-performing investors instead of including all listed CEFs. Great performing private CEFs, family offices, private investors, and hedge funds invest in the public market. Including these investors' holdings may increase the model's ability to pick good equities. However, it might also confuse the model since we aimed to replicate the strategy of a particular investor group, and we have provided evidence that the CEFs' strategies differ from, e.g., private equity investors and activist hedge funds.

We have enlarged the existing literature across multiple research fields by successfully decoding and implementing the CEFs' strategies when investing in public equities. By presenting our findings, we aim to inspire further research and discussions, as well as enhance the understanding of the immense value-creation by Swedish closed-end funds and market outperformance by following a winning strategy.

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9 Appendix

Appendix 1 - Qualitative Assessment of CEF Strategies

Investor

Investor was founded in 1916 by the Wallenberg family because of a newly introduced Swedish law that prohibited banks from owning shares in industrial companies (Investor, 2023a). Today's important holdings, SEB and Atlas Copco, have been a part of the portfolio since the beginning. Investor invests in high-quality companies focusing on long-term trends, such as new technology and sustainability (Investor, 2023b). Investor explains its value creation by:

- Long-term perspective
- Strong network of people
- Engaged ownership with a value-driven culture, a proven governance model and a buy-to-build philosophy.

We interpret Investor's strategy as more focused on active ownership than the investment process itself.

Latour

Latour was founded in 1985 by the Douglas family, still the largest owner (Latour, 2023a). The company focuses on long-term value creation with an overarching strategy to invest in sustainable companies with their own products, high development potential, and which are supported by global megatrends (Latour, 2023b). Latour also wants to avoid the risk of decreasing value. Latour has defined three investment criteria:

- Market and trends:
    - Addresses identified trends
    - The industry shows profitable growth
- Development potential:
    - The next development wave has started
    - Potential for geographical expansion
    - Sustainable business with high ethics
    - Latour can add value
- Companies and market position
    - Development and production of own products with their own brands
    - Sustainable products with high value added

- Good position in the value chain
- Good management

Decentralised ownership is an important part of Latour's model, exemplified by the chief investment officer Johan Menkcel: "Since we acquire companies that already do well, it is important that we let the management continue with its strategy" (Latour, 2023c, p.14). When the current CEO Johan Hjertsson explains Latour's great development over time, he mentions, "We acquire companies to keep and develop, not eventually selling them. Our Focus is always long-term value creation" (Latour, 2023c, p.10).

Industrivärden

Industrivärden was founded in 1944 as a spin-off of Handelsbanken's public holdings. Many holdings, such as SCA and Ericsson, have been in the portfolio since the 1940-1950s (Industrivärden, 2023a). Industrivärden owns substantial ownership stakes and uses active ownership to create long-term value (Industrivärden, 2023b). Industrivärden owns companies with:

- Good market positions
- Strong cash flows
- Financial strength
- Proven business models
- Focus on innovation and development.

The current CEO Helena Stjernholm expressed it as: "Actively owned quality companies create good value potential" (Industrivärden, 2023c, p.8).

Kinnevik

Kinnevik was founded as an investment company in 1936 with investments in iron, paper, and woodworking (Kinnevik, 2023a). Today, the company invest with a long-term strategic perspective in high-growth companies and disruptive technology (Kinnevik, 2023b). The current CEO Georgi Ganev describes it as:

> While valuations are always important when we invest, our primary focus when assessing younger, private companies is to make sure we support the best founders and teams and help build companies addressing large markets with a

> superior offering. This is key to continued long-term value creation for our shareholders (Kinnevik, 2022, p.2)

Svolder

Svolder was founded in 1993 by several asset management firms who wanted to capitalise on the fact that small companies were cheaper than large at the time (Svolder, 2023a). Today, Svolder invests in small and medium-sized companies as they are often overlooked (Svolder, 2023b). Svolder expresses its investment criteria as follows:

- Quality
- Proven business models
- Industry-leading
- Profitable over time
- Dividends are central – not only today's yield but also expected dividend growth
- Long-term growth potential

Bure Equity

Bure Equity was founded in 1992 and originates from the dismantled Swedish employee funds (Bure Equity, 2023). Bure is a long-term focused and engaged owner with at least a 3-5-year horizon (Bure Equity, 2022). The company seeks special situations in different industries, cycles, assets, and phases and could therefore be considered a generalist. When investing, they analyse the following:

- The market
- Business model
- Financial position
- Management and board

Bure Equity does not express its investment strategy much but focuses more on responsible ownership.

Traction

Traction was founded in 1974 by Bengt Stillström as a one-person consultancy firm (Traction, 2023). Today, the company invests in small and medium-sized companies focusing on active ownership and developing the business (Traction, 2022). Traction seeks investments with substantial potential for revaluation with limited risks.

Spiltan

Spiltan was founded in 1986 as an investments club and today invests broadly in growth companies as active owners (Spiltan, 2023a). Spiltan (2023b) has the following investment criteria:

- Team – knowledgeable, passionate and driven
- Sustainable business model
- Industry: Tech (primarily), finance, real estate, and industrials.
- Scalable business model in growing industries

In a news article, the founder and CEO, Per H Börjesson, further explains that Spiltan looks for:

- Substantial ownership of the founder
- Growth potential
- Profitability
- Good business model (Realtid, 2017)

Creades

Creades was founded in 2012 as Öresund was divided into two firms (Creades, 2023a). The firm takes a long-term view, without an exit strategy, in small- and mid-sized companies with substantial potential for revaluation and underlying value creation (Creades, 2023b). According to Creades (2023c), the public portfolio strategy contains both long-term holdings focusing on active ownership, and a more active strategy of finding fundamentally undervalued companies, exciting growth opportunities or special situations.

Lundbergsföretagen

Lundbergs was founded in 1944 as a homebuilder, and a large part of the portfolio is still real estate (Lundbergsföretagen, 2023a). The company invests in high-quality companies with low risk with the following criteria:

- Good market positions
- Stable and strong cash flows
- Own products and brands

The current CEO Fredrik Lundberg mentions that the investment process is a combination of finding fundamentally great companies and using experience:

> As investors, it is of course important to always choose healthy and good companies with great foundations for the future. The reasons behind choosing companies should be moderately rational, i.e., it is also important to invest with its senses. As a long-term active investor, you live long and close to your companies. (Lundbergsföretagen, 2023b, p.7)

Öresund

Öresund was founded in 1956 by a merger of three insurance companies (Öresund, 2023a) and is today associated with the chairman and largest owner, Mats Qviberg. Öresund (2023b) is an active owner and invests in companies with good potential risk/reward with the following criteria:

- Attractive valuation
- Profitability
- Stable cash flows
- Dividends

The company also states investing a part of its portfolio in companies with strong growth potential, even if the dividend capacity is limited. In the annual report, chairman Mats Qviberg and CEO Nicklas Paulsson comment on the investment strategy:

> Opportunities are created in challenging times for firms with financial flexibility. It is even more essential to choose portfolio companies with proven and competitive business models where cash flows and profitability are prioritised. (Öresund, 2023b, p.5-6)

Byggmästare AJ Ahlström

Byggmästare AJ Ahlström was founded in 1898 as a building and real estate company but did in 2018 pivot the business into a broader investment firm (Byggmästare AJ Ahlström, 2023a). The company are long-term active owners in small- and mid-sized companies with ambitions of being leaders in their niche (Byggmästare AJ Ahlström, 2023b). The company further targets investments with proven, sustainable, and scalable business models with a valuation-driven approach. Chairman Mikael Ahlström and CEO Tomas Bergström expressed it as: "With established terminology, you could say we are primarily value investors" (Byggmästare AJ Ahlström, 2022).

Appendix 2 – KPI Definitions

Price/Earnings (P/E): *Stock price divided by earnings per share.*

Price/Book (P/B): *Stock price divided by book value per share.*

EV/EBIT: *Enterprise Value divided by Earnings Before Interest and Taxes.*

EV/EBITDA: *Enterprise Value divided by Earnings Before Interest, Taxes, Depreciation and Amortisation.*

EV/Sales (EV/S): *Enterprise Value divided by Revenue*

FCF Yield: *Free Cash Flow divided by Market Cap*

Dividend Yield: *Dividend per share divided by Market Cap*

Return on Equity (ROE): *Earnings divided by Total Equity*

Operating Return on Assets (ROA): *EBIT divided by Total Revenue*

Return on Invested Capital (ROIC): *Net Operating Profits after Tax divided by Invested Capital*

EBIT margin: *EBIT divided by Revenue*

Profit margin: *Earnings divided by Revenue*

Profitable Binary: *1 if the company has a positive Profit margin and 0 otherwise*

Debt/Equity: *Total Debt divided by Total Equity*

Net Debt/EBITDA: *(Total Debt – Cash and Cash Equivalents) divided by EBITDA*

EBIT/Interest Expense (Interest Coverage Ratio): *EBIT divided by Total Interest Expense*

Market Cap: *Total market value of the company = Total Shares Outstanding * Stock Price*

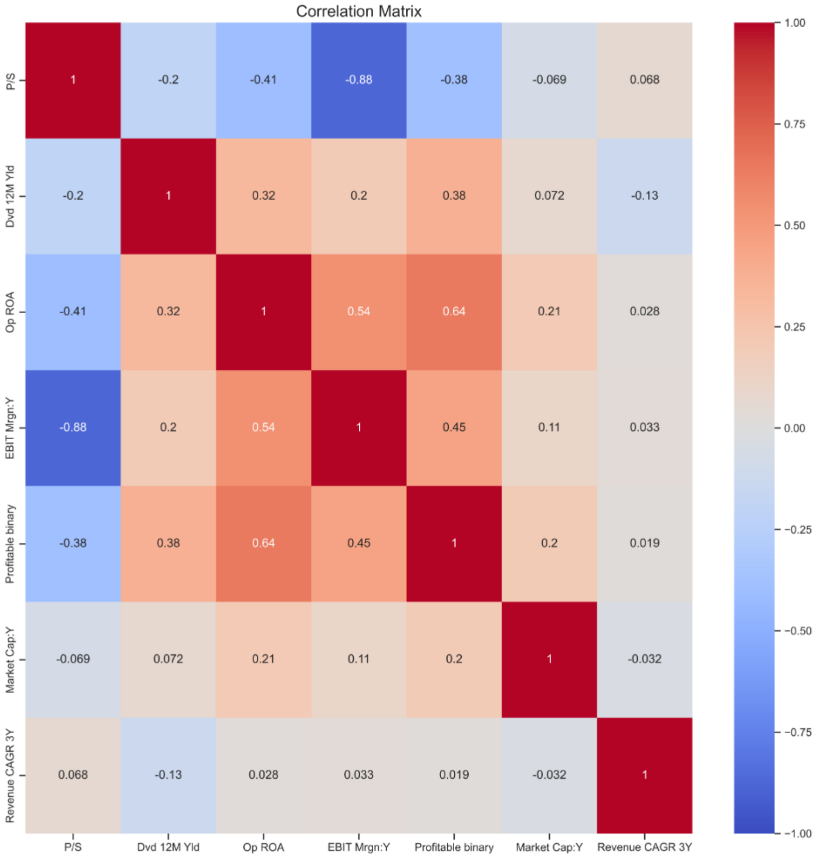
Revenue CAGR 3Y: *Compounded Annual Growth Rate in Revenue over the last three years*

Analyst Recommendations: *Total number of analysts covering the stock with an active recommendation*

Cash/Revenue: *Cash and Cash Equivalents divided by Revenue*

Appendix 3 – Econometric Robustness

The correlation matrix below displays the correlation between the final predictors used in the logit regression. We have decided to keep P/S and EBIT Margin which has a correlation north of 0.7, and instead conduct a VIF-test to ensure that we have limited multicollinearity between the two predictors. We believe both predictors are important to predict what firms CEFs typically target.

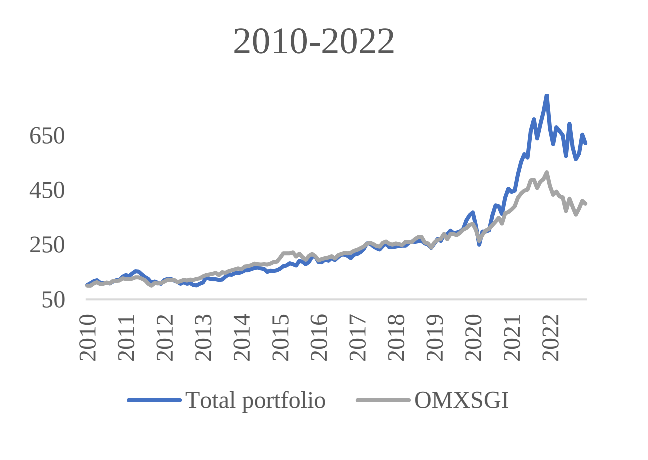


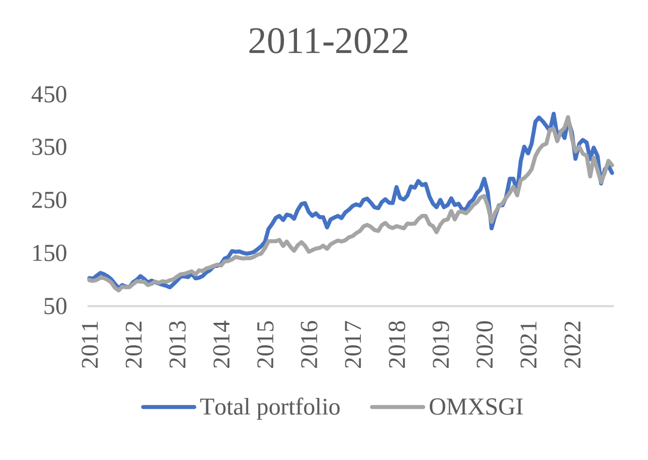
The VIF test results are presented below, and we can observe that each predictor's values are below 10. Hence, we can conclude that we do not have problematic autocorrelation in the final specified model.

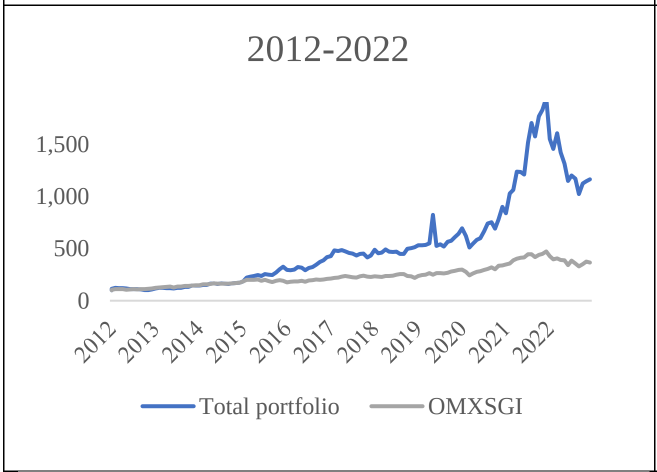
Variance Inflation Test (VIF)	
P/S	4,89
Dividend Yield	1,21
Operating ROA	2,11
EBIT Margin	5,73
Profitable Binary	1,87
Market Cap	1,06
Revenue CAGR 3Y	1,07

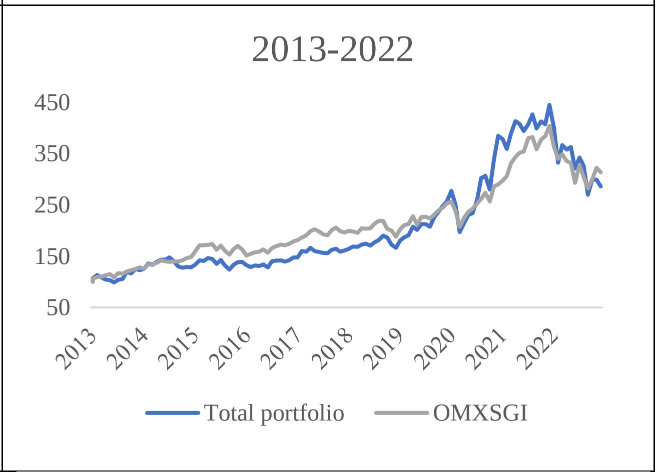
Appendix 4 – Charts of the portfolios' performances

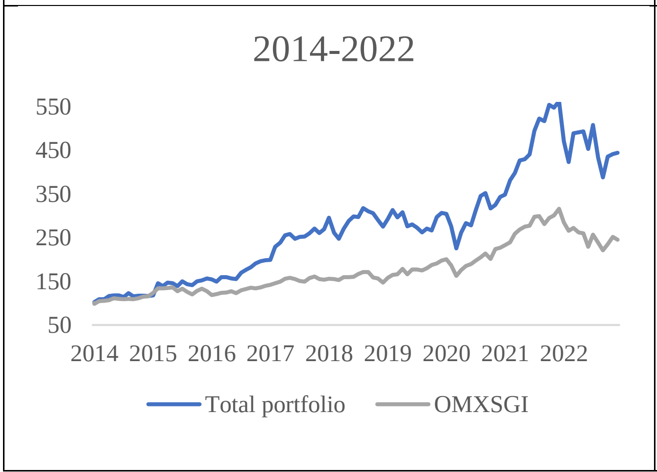
The following charts show the performance of all synthetic portfolios created in the Swedish market compared with the index OMXSGI. The first portfolio started in 2010, and the last in 2018, with all ending in 2022. The index is 100, i.e., it could be seen as 100 SEK invested in either the portfolio or the index at the start date. Both our portfolio and OMXSGI account for reinvested dividends.

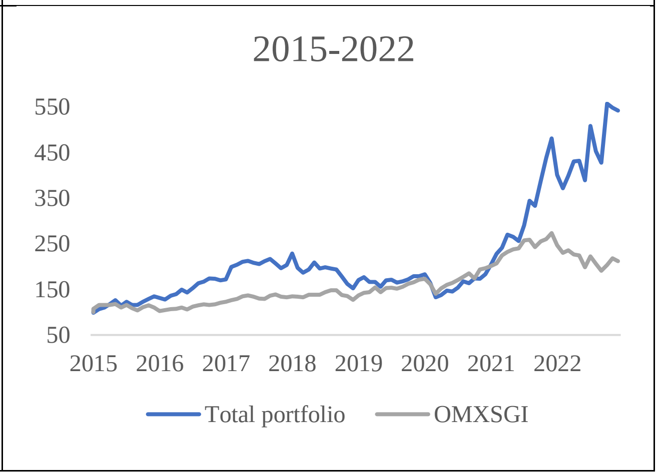


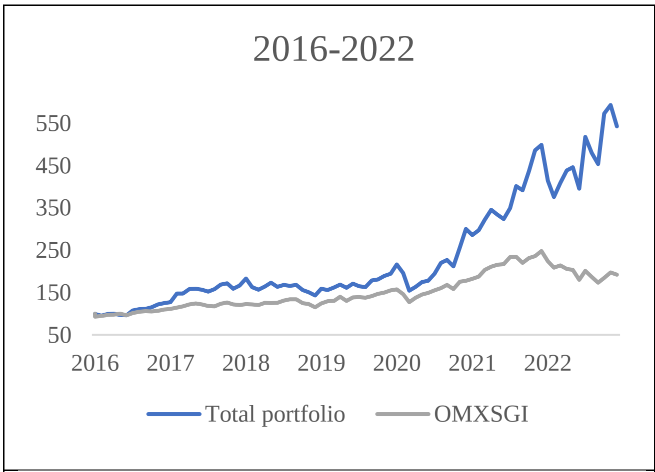


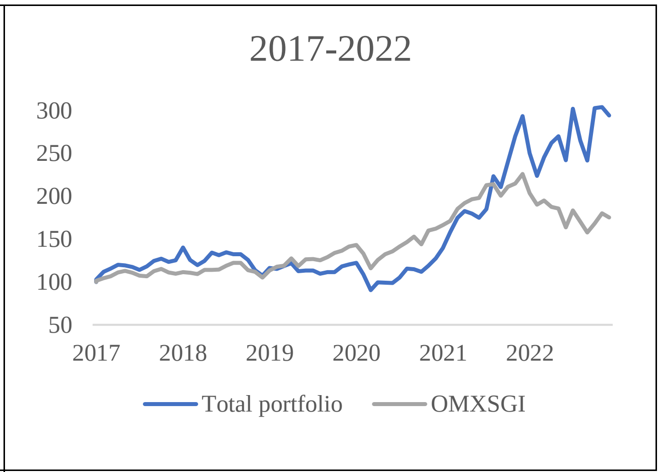


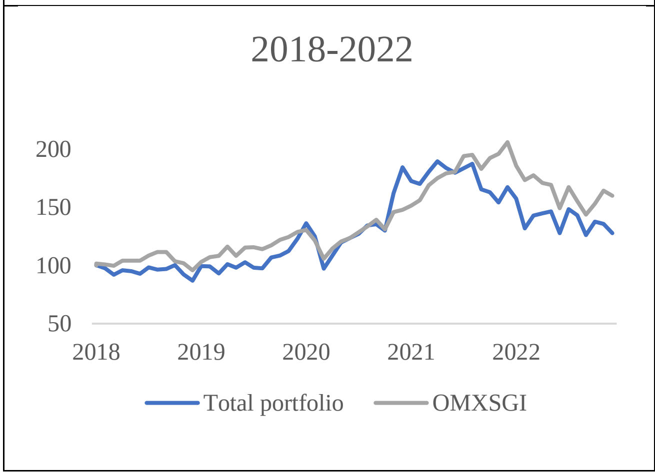




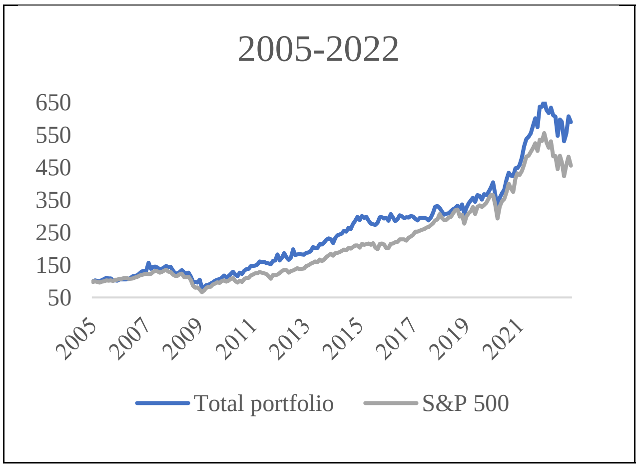


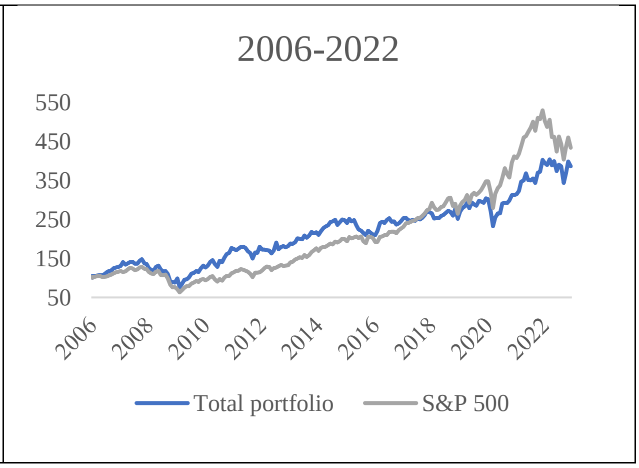


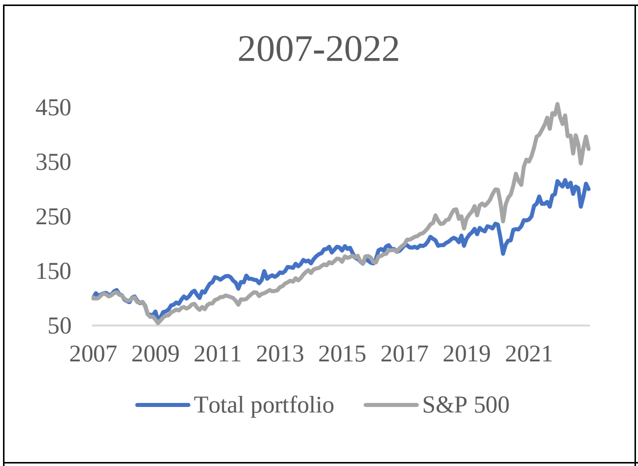


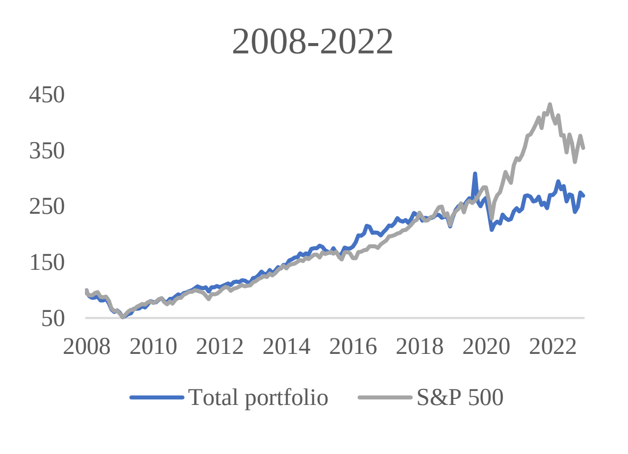


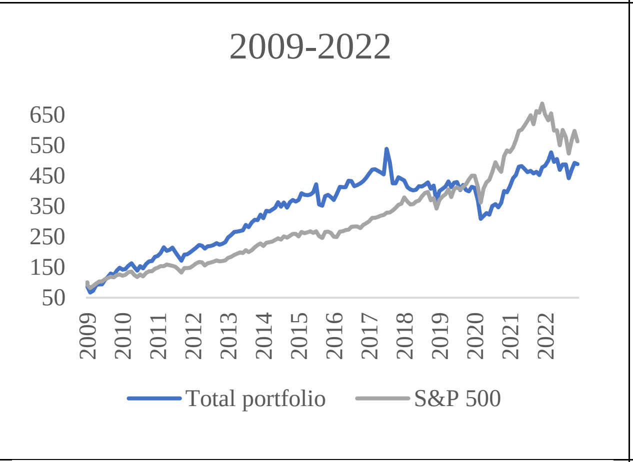
The following charts show the performance of all synthetic portfolios created in the US market compared with the S&P 500. The first portfolio starts in 2005 and the last in 2018, with all ending in 2022. The index is 100, i.e., it could be seen as 100 SEK invested in either the portfolio or the index at the start date. Both our portfolio and S&P 500 account for reinvested dividends.

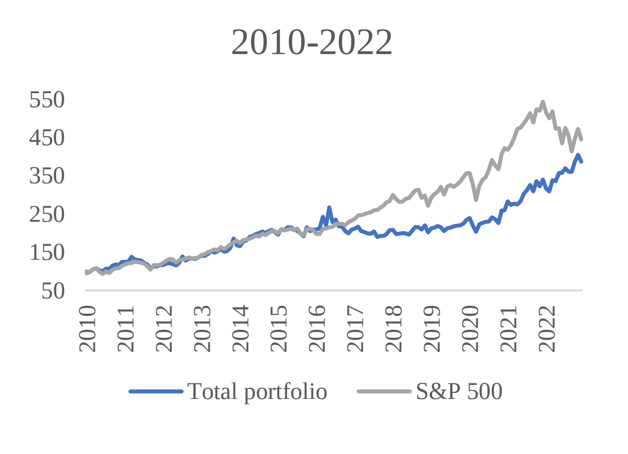


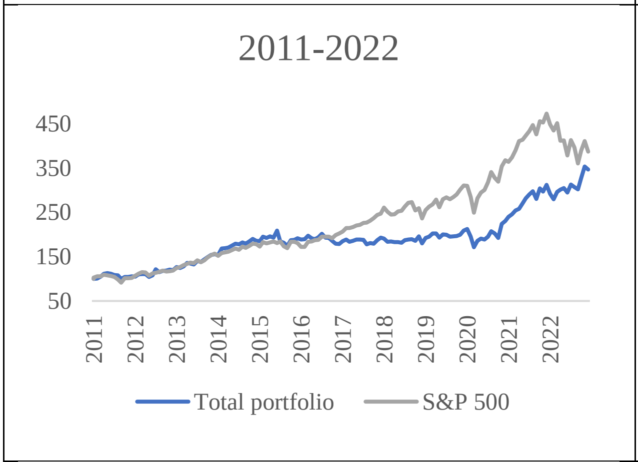


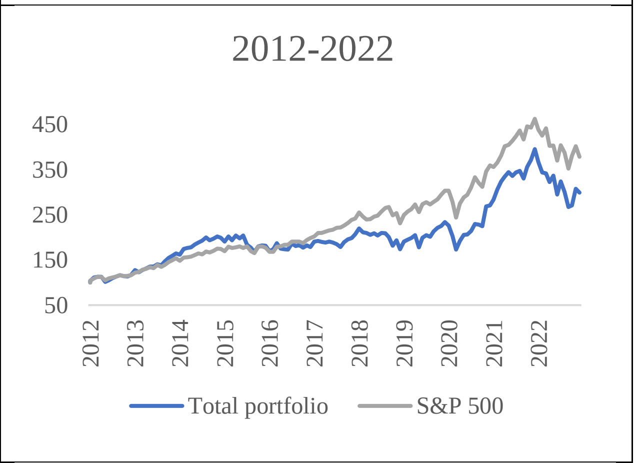

2007-2022
450
350
250
150
50
2007 2009 2011 2013 2015 2017 2019 2021
Total portfolio
S&P 500

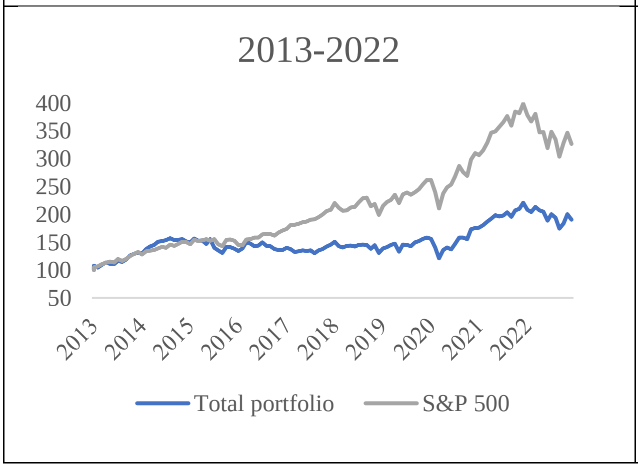

2008-2022
450
350
250
150
50
2008 2010 2012 2014 2016 2018 2020 2022
Total portfolio
S&P 500

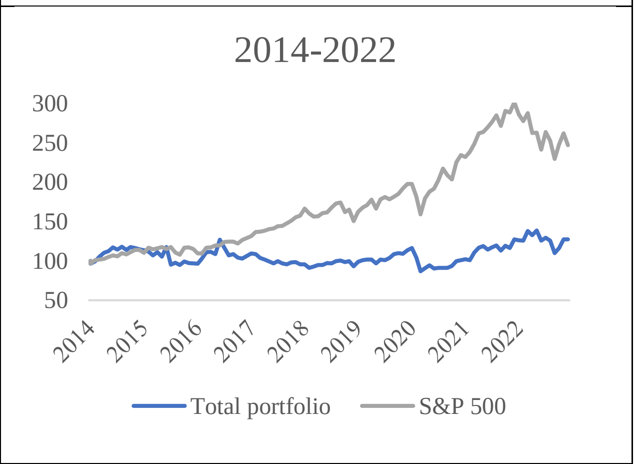

2009-2022
650
550
450
350
250
150
50
2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
Total portfolio
S&P 500

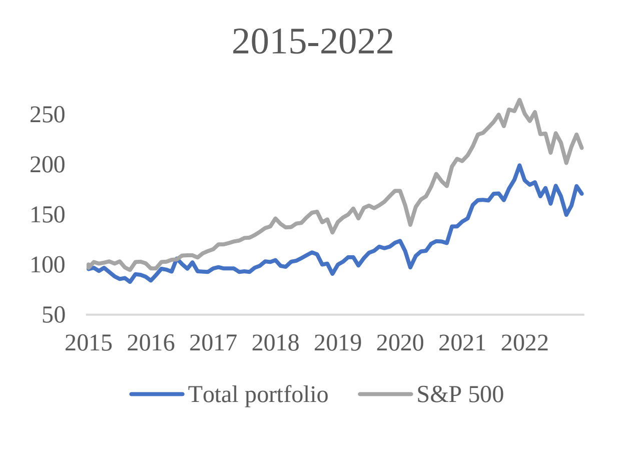

2010-2022
550
450
350
250
150
50
2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
Total portfolio
S&P 500

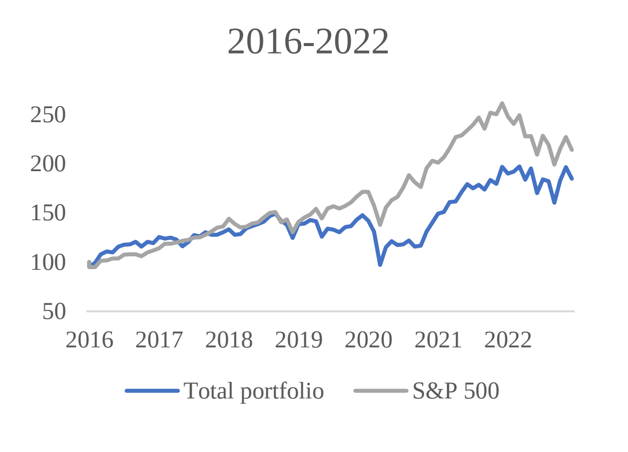

2011-2022
450
350
250
150
50
2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
Total portfolio
S&P 500

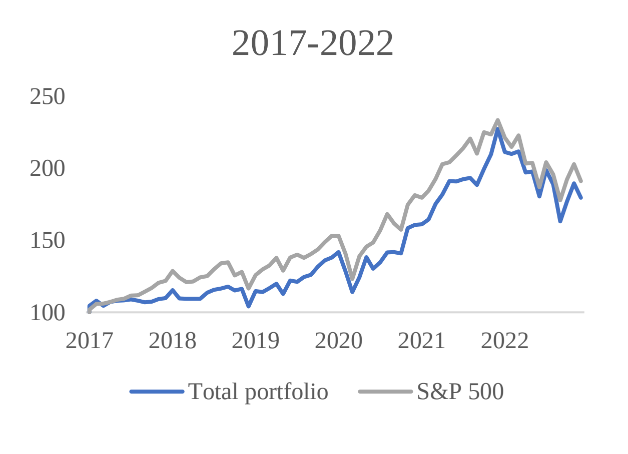

2012-2022
450
350
250
150
50
2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
Total portfolio
S&P 500

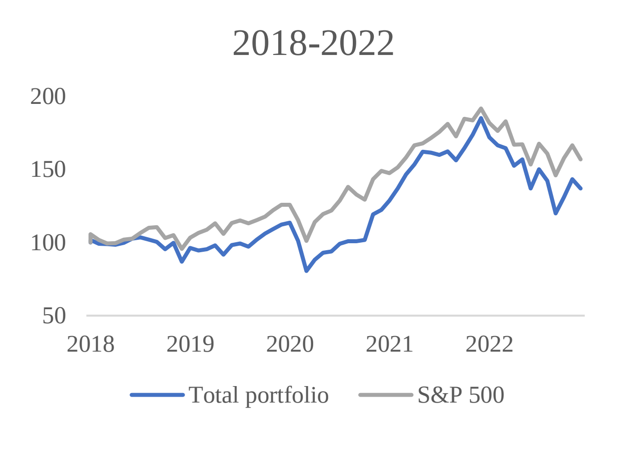

2013-2022
400
350
300
250
200
150
100
50
2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
Total portfolio
S&P 500


2014-2022
300
250
200
150
100
50
2014 2015 2016 2017 2018 2019 2020 2021 2022
Total portfolio
S&P 500


2015-2022
250
200
150
100
50
2015 2016 2017 2018 2019 2020 2021 2022
Total portfolio
S&P 500


2016-2022
250
200
150
100
50
2016 2017 2018 2019 2020 2021 2022
Total portfolio
S&P 500


2017-2022
250
200
150
100
2017 2018 2019 2020 2021 2022
Total portfolio
S&P 500


2018-2022
200
150
100
50
2018 2019 2020 2021 2022
Total portfolio
S&P 500

Appendix 5 – Fama French 3 Factor Model Sweden Regression Output

2010-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.750528001
R Square	0.563292281
Adjusted R Square	0.55467305
Standard Error	0.044107903
Observations	156

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.381433949	0.12714465	65.35296032	3.36541E-27
Residual	152	0.295717082	0.001945507		
Total	155	0.677151031			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0.006510104	0.003568518	1.824315954	0.070068107	-0.000540195	0.013560404	-0.000540195	0.013560404
X Variable 1	0.902372654	0.073015521	12.35864153	9.98703E-25	0.758116332	1.046628976	0.758116332	1.046628976
X Variable 2	1.058943821	0.20767134	5.099133176	1.0019E-06	0.648648815	1.469238827	0.648648815	1.469238827
X Variable 3	-0.582273856	0.131065679	-4.442611223	1.70241E-05	-0.841219521	-0.32332819	-0.841219521	-0.32332819

2011-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.746147918
R Square	0.556736715
Adjusted R Square	0.547238216
Standard Error	0.043144372
Observations	144

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.327313902	0.109104634	58.61312591	1.31487E-24
Residual	140	0.260601163	0.001861437		
Total	143	0.587915065			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0.004067044	0.003624327	1.122151509	0.263718906	-0.003098445	0.011232533	-0.003098445	0.011232533
X Variable 1	0.887608305	0.077035849	11.52201624	5.08108E-22	0.735304293	1.039912317	0.735304293	1.039912317
X Variable 2	0.88447618	0.213652056	4.139797195	5.97574E-05	0.462074589	1.306877772	0.462074589	1.306877772
X Variable 3	0.042628914	0.129955869	0.328026082	0.743382007	-0.214300819	0.299558648	-0.214300819	0.299558648

2012-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.462032646
R Square	0.213474166
Adjusted R Square	0.195039967
Standard Error	0.080241941
Observations	132

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.223689269	0.07456309	11.58033302	9.12448E-07
Residual	128	0.824162435	0.006438769		
Total	131	1.047851704			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0.015794856	0.007065046	2.235633779	0.02710842	0.001815455	0.029774257	0.001815455	0.029774257
X Variable 1	0.633832356	0.155095187	4.086731302	7.67146E-05	0.32695003	0.940714681	0.32695003	0.940714681
X Variable 2	1.453755636	0.41695229	3.486623457	0.000670796	0.628744293	2.278766979	0.628744293	2.278766979
X Variable 3	-0.16482688	0.249999719	-0.659308263	0.510882258	-0.659494037	0.329840276	-0.659494037	0.329840276

2013-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.752565917
R Square	0.566355459
Adjusted R Square	0.555140514
Standard Error	0.042828553
Observations	120

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.277894537	0.092631512	50.50006555	5.88928E-21
Residual	116	0.212777059	0.001834285		
Total	119	0.490671595			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0.004074473	0.003945701	1.032636044	0.303922385	-0.003740485	0.01188943	-0.003740485	0.01188943
X Variable 1	0.978979632	0.087168496	11.23088824	2.9547E-20	0.806331443	1.151627821	0.806331443	1.151627821
X Variable 2	0.645958019	0.239158614	2.700960704	0.007949995	0.172274249	1.11964179	0.172274249	1.11964179
X Variable 3	-0.181061908	0.136750975	-1.324026451	0.188097358	-0.451914445	0.089790629	-0.451914445	0.089790629

2014-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.705178356
R Square	0.497276514
Adjusted R Square	0.482774875
Standard Error	0.049577708
Observations	108

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.252857014	0.084285671	34.29105586	1.71818E-15
Residual	104	0.255626711	0.002457949		
Total	107	0.508483725			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0.011161926	0.004795728	2.327472882	0.021876978	0.001651818	0.020672034	0.001651818	0.020672034
X Variable 1	0.93362992	0.104710181	8.9163242	1.75939E-14	0.725985701	1.141274138	0.725985701	1.141274138
X Variable 2	0.689126513	0.288862128	2.385658925	0.018857953	0.116302074	1.261950953	0.116302074	1.261950953
X Variable 3	-0.43803239	0.164581613	-2.661490438	0.009014074	-0.764403906	-0.111660875	-0.764403906	-0.111660875

2015-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.585774422
R Square	0.343131673
Adjusted R Square	0.321712054
Standard Error	0.067967419
Observations	96

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.222009663	0.074003221	16.01950379	1.85214E-08
Residual	92	0.42500045	0.00461957		
Total	95	0.647010112			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0.01527731	0.006985337	2.187054089	0.031274247	0.001403828	0.029150792	0.001403828	0.029150792
X Variable 1	0.917649025	0.14902245	6.157790477	1.91025E-08	0.621677576	1.213620475	0.621677576	1.213620475
X Variable 2	0.465075316	0.425200317	1.093779325	0.276907355	-0.379409216	1.309559848	-0.379409216	1.309559848
X Variable 3	-0.518422939	0.231542603	-2.238995907	0.027566938	-0.978286534	-0.058559345	-0.978286534	-0.058559345

2016-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.677822284
R Square	0.459443049
Adjusted R Square	0.439172163
Standard Error	0.0638634
Observations	84

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.277321976	0.092440659	22.66516896	1.01953E-10
Residual	80	0.326282708	0.004078534		
Total	83	0.603604684			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0.017978463	0.007001694	2.567730325	0.012098365	0.004044647	0.031912278	0.004044647	0.031912278
X Variable 1	1.097226774	0.15106298	7.263373032	2.20336E-10	0.796601864	1.397851685	0.796601864	1.397851685
X Variable 2	0.3928754	0.46081068	0.852574423	0.396440633	-0.524167079	1.309917878	-0.524167079	1.309917878
X Variable 3	-0.36996343	0.225631188	-1.639682147	0.104997998	-0.818983803	0.079056943	-0.818983803	0.079056943

2017-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.633280579
R Square	0.401044292
Adjusted R Square	0.374619775
Standard Error	0.065115442
Observations	72

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.193052097	0.064350699	15.17697744	1.1613E-07
Residual	68	0.28832141	0.004240021		
Total	71	0.481373506			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0.012360107	0.007735318	1.597879614	0.114706628	-0.00307548	0.027795694	-0.00307548	0.027795694
X Variable 1	0.927973192	0.16078307	5.771585235	2.12177E-07	0.607135572	1.248810813	0.607135572	1.248810813
X Variable 2	0.50502801	0.49431442	1.021673634	0.310556471	-0.481361057	1.491417077	-0.481361057	1.491417077
X Variable 3	-0.36918224	0.242258353	-1.523919546	0.132166299	-0.852601258	0.114236778	-0.852601258	0.114236778

2018-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.769513502
R Square	0.59215103
Adjusted R Square	0.570301978
Standard Error	0.053798417
Observations	60

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.235320702	0.078440234	27.10190951	5.84859E-11
Residual	56	0.1620791	0.00289427		
Total	59	0.397399801			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0.005410654	0.006983186	0.774811773	0.441710258	-0.008578347	0.019399656	-0.008578347	0.019399656
X Variable 1	0.974476443	0.1361589	7.156905964	1.9049E-09	0.70171739	1.247235495	0.70171739	1.247235495
X Variable 2	0.936542415	0.429241107	2.1818563	0.033332795	0.07666915	1.796415679	0.07666915	1.796415679
X Variable 3	0.152094764	0.205007486	0.741898583	0.46124914	-0.25858458	0.562774108	-0.25858458	0.562774108

Appendix 6 – Fama French 3 Factor Model US Regression Output

2005-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.682559492
R Square	0.46588746
Adjusted R Square	0.458329264
Standard Error	0.036527941
Observations	216

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.246737119	0.082245706	61.64003161	1.07687E-28
Residual	212	0.282869578	0.00133429		
Total	215	0.529606697			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0.001776124	0.002520081	0.704788682	0.481715308	-0.003191502	0.00674375	-0.003191502	0.00674375
X Variable 1	0.771179079	0.059102329	13.04820121	5.93598E-29	0.654675563	0.887682596	0.654675563	0.887682596
X Variable 2	-0.214359213	0.110201686	-1.945153662	0.053078872	-0.431590651	0.002872225	-0.431590651	0.002872225
X Variable 3	0.047040151	0.079380918	0.592587638	0.554088696	-0.109436865	0.203517167	-0.109436865	0.203517167

2006-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.746080622
R Square	0.556636294
Adjusted R Square	0.549985838
Standard Error	0.033890916
Observations	204

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.288408459	0.096136153	83.69897169	4.02328E-35
Residual	200	0.229718839	0.001148594		
Total	203	0.518127297			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-4.16522E-05	0.002407843	-0.017298541	0.986215694	-0.004789668	0.004706364	-0.004789668	0.004706364
X Variable 1	0.801017499	0.055116508	14.53316845	3.8892E-33	0.692333464	0.909701533	0.692333464	0.909701533
X Variable 2	-0.110248019	0.103846595	-1.061643083	0.289678032	-0.315022727	0.094526689	-0.315022727	0.094526689
X Variable 3	0.169595596	0.074205465	2.28548659	0.023332813	0.023270119	0.315921073	0.023270119	0.315921073

2007-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.752786627
R Square	0.566687706
Adjusted R Square	0.559773148
Standard Error	0.033988816
Observations	192

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.284035552	0.094678517	81.95573976	6.00413E-34
Residual	188	0.217185048	0.00115524		
Total	191	0.5012206			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0.000662225	0.002489307	-0.266027866	0.790509271	-0.005572789	0.004248339	-0.005572789	0.004248339
X Variable 1	0.803099967	0.05543944	14.48607645	1.98954E-32	0.693736652	0.912463283	0.693736652	0.912463283
X Variable 2	-0.141710556	0.107433375	-1.319055243	0.188755011	-0.353640366	0.070219254	-0.353640366	0.070219254
X Variable 3	0.161454894	0.075151127	2.148402831	0.032961093	0.013207069	0.309702719	0.013207069	0.309702719

2008-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.671714418
R Square	0.45120026
Adjusted R Square	0.441845719
Standard Error	0.036521335
Observations	180

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.193001815	0.064333938	48.23328679	8.41561E-23
Residual	176	0.234750188	0.001333808		
Total	179	0.427752003			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0.00015682	0.002759687	-0.056825286	0.954748832	-0.005603157	0.005289517	-0.005603157	0.005289517
X Variable 1	0.658920205	0.060277331	10.93147623	1.47253E-21	0.539960821	0.77787959	0.539960821	0.77787959
X Variable 2	-0.176864233	0.116940841	-1.512424844	0.132219361	-0.407651003	0.053922538	-0.407651003	0.053922538
X Variable 3	0.202290431	0.081399999	2.485140448	0.013883754	0.041644733	0.362936129	0.041644733	0.362936129

2009-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.774595316
R Square	0.599997904
Adjusted R Square	0.592680792
Standard Error	0.038585883
Observations	168

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.366258915	0.122086305	81.99928382	1.86747E-32
Residual	164	0.244174743	0.00148887		
Total	167	0.610433658			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0.000422414	0.003071602	-0.137522281	0.890786677	-0.006487398	0.005642571	-0.006487398	0.005642571
X Variable 1	0.9151585	0.069846192	13.10248231	2.6843E-27	0.777244778	1.053072222	0.777244778	1.053072222
X Variable 2	0.058525246	0.127123001	0.460382825	0.645851303	-0.192483514	0.309534006	-0.192483514	0.309534006
X Variable 3	0.36920384	0.089311233	4.133901496	5.67811E-05	0.192855722	0.545551958	0.192855722	0.545551958

2010-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.582500668
R Square	0.339307028
Adjusted R Square	0.326267036
Standard Error	0.042356016
Observations	156

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.140044793	0.046681598	26.02049189	1.21803E-13
Residual	152	0.272692878	0.001794032		
Total	155	0.412737671			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0.001160564	0.003487793	0.332750275	0.739781281	-0.005730248	0.008051376	-0.005730248	0.008051376
X Variable 1	0.697793716	0.08116888	8.596813436	9.31168E-15	0.537428853	0.858158579	0.537428853	0.858158579
X Variable 2	-0.143103153	0.148157308	-0.965886561	0.3356352	-0.435816648	0.149610342	-0.435816648	0.149610342
X Variable 3	-0.022488801	0.105643055	-0.212875335	0.831709432	-0.231207142	0.186229541	-0.231207142	0.186229541

2011-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.695092531
R Square	0.483153626
Adjusted R Square	0.472078347
Standard Error	0.030525781
Observations	144

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.121950999	0.040650333	43.62450892	5.72666E-20
Residual	140	0.130455259	0.000931823		
Total	143	0.252406258			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0.001242123	0.002620447	0.474011957	0.636229802	-0.003938641	0.006422887	-0.003938641	0.006422887
X Variable 1	0.674261971	0.061729237	10.92289499	1.79808E-20	0.552219954	0.796303989	0.552219954	0.796303989
X Variable 2	-0.041063511	0.110481731	-0.371676937	0.710695326	-0.259491828	0.177364805	-0.259491828	0.177364805
X Variable 3	0.041183142	0.078103269	0.527290889	0.598826194	-0.113231217	0.195597502	-0.113231217	0.195597502

2012-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.842730333
R Square	0.710194414
Adjusted R Square	0.703402096
Standard Error	0.030126949
Observations	132

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.284702171	0.094900724	104.5584688	2.88373E-34
Residual	128	0.116177032	0.000907633		
Total	131	0.400879203			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	-0.002953517	0.002707656	-1.090802251	0.277409014	-0.008311078	0.002404043	-0.008311078	0.002404043
X Variable 1	1.060740652	0.063339558	16.74689066	4.738E-34	0.935412515	1.186068789	0.935412515	1.186068789
X Variable 2	-0.013232265	0.110931596	-0.119283101	0.905238081	-0.232729381	0.206264851	-0.232729381	0.206264851
X Variable 3	0.205843754	0.077726902	2.648294833	0.009107809	0.052047798	0.35963971	0.052047798	0.35963971

2013-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.841098488
R Square	0.707446667
Adjusted R Square	0.699880633
Standard Error	0.025057812
Observations	120

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.176129837	0.058709946	93.50296643	8.0023E-31
Residual	116	0.072835696	0.000627894		
Total	119	0.248965533			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0.004142888	0.002355241	-1.759007762	0.081212998	-0.00880774	0.000521964	-0.00880774	0.000521964
X Variable 1	0.870570912	0.053949796	16.13668599	1.98854E-31	0.763716544	0.97742528	0.763716544	0.97742528
X Variable 2	-0.1148086	0.093591396	-1.226700364	0.222419294	-0.300178152	0.070560953	-0.300178152	0.070560953
X Variable 3	0.147253447	0.065400606	2.251560909	0.026232767	0.017719307	0.276787587	0.017719307	0.276787587

2014-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.569795358
R Square	0.32466675
Adjusted R Square	0.305185984
Standard Error	0.043726695
Observations	108

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.095597452	0.031865817	16.66601492	6.49408E-09
Residual	104	0.198850477	0.001912024		
Total	107	0.294447929			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0.002924938	0.00429811	-0.680517304	0.497689204	-0.011448251	0.005598375	-0.011448251	0.005598375
X Variable 1	0.586438256	0.096178951	6.097365896	1.85861E-08	0.395711787	0.777164725	0.395711787	0.777164725
X Variable 2	-0.099251694	0.16631933	-0.596753811	0.551968623	-0.429069168	0.230565779	-0.429069168	0.230565779
X Variable 3	0.368139509	0.114823701	3.206128232	0.001787586	0.140439801	0.595839217	0.140439801	0.595839217

2015-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.7875049
R Square	0.620163967
Adjusted R Square	0.60777801
Standard Error	0.035064228
Observations	96

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.184682934	0.061560978	50.069925	2.80433E-19
Residual	92	0.11311401	0.0012295		
Total	95	0.297796944			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0.002195397	0.003641357	-0.602906209	0.548054456	-0.009427446	0.005036653	-0.009427446	0.005036653
X Variable 1	0.92917757	0.078344793	11.8601063	3.09049E-20	0.773578049	1.084777091	0.773578049	1.084777091
X Variable 2	-0.083185554	0.142614137	-0.583291083	0.561124544	-0.36642954	0.200058432	-0.36642954	0.200058432
X Variable 3	0.09359262	0.093749015	0.998331777	0.320737088	-0.092601015	0.279786256	-0.092601015	0.279786256

2016-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.89123832
R Square	0.794305743
Adjusted R Square	0.786592208
Standard Error	0.028810995
Observations	84

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.256431898	0.085477299	102.9755849	2.17655E-27
Residual	80	0.066405876	0.000830073		
Total	83	0.322837774			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0.001835775	0.003207838	-0.572277786	0.568738545	-0.008219577	0.004548027	-0.008219577	0.004548027
X Variable 1	0.996591614	0.067940672	14.66855682	2.17095E-24	0.861385367	1.131797861	0.861385367	1.131797861
X Variable 2	0.329706509	0.126181181	2.612961034	0.010719351	0.078597956	0.580815061	0.078597956	0.580815061
X Variable 3	0.420018724	0.07857622	5.345366893	8.31563E-07	0.263647063	0.576390385	0.263647063	0.576390385

2017-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.872245828
R Square	0.760812784
Adjusted R Square	0.750260407
Standard Error	0.026331693
Observations	72

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.149970662	0.049990221	72.0987103	4.39143E-21
Residual	68	0.047148347	0.000693358		
Total	71	0.197119009			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0.000487947	0.003169718	-0.153940243	0.878112809	-0.00681302	0.005837126	-0.00681302	0.005837126
X Variable 1	0.91182741	0.063308405	14.40294407	2.44214E-22	0.785497456	1.038157365	0.785497456	1.038157365
X Variable 2	-0.18472802	0.122720393	-1.505275649	0.136884372	-0.429612752	0.060156712	-0.429612752	0.060156712
X Variable 3	0.070107634	0.075664324	0.926561295	0.357431297	-0.080878174	0.221093443	-0.080878174	0.221093443

2018-2022

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.917948454
R Square	0.842629364
Adjusted R Square	0.834198794
Standard Error	0.027236726
Observations	60

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.222438896	0.074146299	99.94927774	1.8191E-22
Residual	56	0.041542999	0.000741839		
Total	59	0.263981894			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0.001580032	0.003557239	-0.44417373	0.658628733	-0.008706038	0.005545974	-0.008706038	0.005545974
X Variable 1	1.016896481	0.066328045	15.33131992	1.06842E-21	0.88402544	1.149767522	0.88402544	1.149767522
X Variable 2	0.153017115	0.134741384	1.135635622	0.260946124	-0.116902311	0.422936542	-0.116902311	0.422936542
X Variable 3	0.383838592	0.080234875	4.78393707	1.2916E-05	0.223108823	0.54456836	0.223108823	0.54456836