COMBINING VALUE AND QUALITY ON THE SWEDISH EQUITY MARKET

DOES IT HOLD OVER TIME?

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Abstract:

The ultimate goal of many investors is to achieve alpha. Yet, most of them are unable to do this on average. Strategies achieving anomalous effects relating to e.g. size and value are often discussed in the literature and are at the core of this study. This paper specifically analyzes Joel Greenblatt's Magic Formula on the Stockholm Stock Exchange for the years between 2004 and 2018. His original approach is to assess stocks on the basis of two key metrics, Return on Invested Capital and Earnings Yield. The main rationalization behind this is to effectively source companies which are of high quality but also relatively undervalued. Moreover, this strategy has allegedly been able to realize returns well beyond the assumed risk and is therefore said to generate positive alpha. Although Greenblatt's original strategy is central to this paper, we distinguish ourselves by applying a weighting system to the two metrics. We have done this in an attempt of increasing the abnormal returns, while still not fully abandoning Greenblatt's original idea. Our results confirm that it is possible to increase the abnormal portfolio returns and we find that the alphas systematically trend upward as we increase the emphasis on Earnings Yield. In the pursuit of realizing higher alpha, we also decrypt the two metric's ability of forecasting returns. The abnormal returns are statistically significant at the 5%-level when applying the Fama-French Three-Factor and Carhart Four-Factor Models.

Keywords:

Magic Formula, Value Investing, Abnormal Returns, Efficient Market Hypothesis, Portfolio Management

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1. Introduction and Background

As financial markets become more developed over time, profit opportunities that allow investors to achieve returns beyond the given risk are known to become less prominent (Bertone et al. 2015). Such opportunities are said to violate the Efficient Market Hypothesis (EMH). For example, inconsistencies such as the January effect, the Small-firm effect, and the Weekend effect has lost most of their predictive power since the time of their first documentation (Moller & Zilca 2008; Schwert 2003; Robins & Smith 2016). In effect, anomalies are becoming increasingly infrequent. However, one interesting and strongly debated investment strategy that allegedly still hold great power is the so-called Magic Formula (MF). This strategy was first shared with the world through Joel Greenblatt's work, *The Little Book that Beats the Market* (2006) and has since been back-tested in multiple reports. Irrespective of geographic market location, the results of these reports are largely uniform and in line with what Greenblatt concluded back in 2006, namely that the EMH need not to hold.

Quite paradoxically, Magic Formula Investing (MFI) is a seemingly basic strategy and includes leveraging both quality and value investing (the latter being derived from Benjamin Graham's ideas and favored by Warren Buffet, among many). Greenblatt's systematic approach to stock-picking involves identifying and buying high-quality stocks that are currently selling at a discount in relation to their intrinsic value (Greenblatt 2006). In turn, this is achieved by means of two key metrics; Return on Invested Capital (RoIC) and Earnings Yield (EY). A high RoIC is positively correlated with the quality of the firm, ceteris paribus (Damodaran 2007). Using the same analogy, a high EY will in general indicate that the stock is selling at a low valuation. This can potentially proxy positive stock performance development in the future (Fama & French 2012).

The MF system rank-orders all sampled stocks on RoIC and EY separately. The sum of these individual scores are then calculated and subsequently ranked again. Depending on the investor's diversification preference, a series of 20–30 stocks is generated on the basis of these final scores. Thus, the investor should in theory receive a portfolio of high-quality firms which are currently selling at low price points. While such a portfolio has been proven to yield outstanding returns, the explanations of those returns remains uncovered. The most common rationalization for higher returns is greater risk. The potential for exceptional returns should then not be a mystery. However, Greenblatt determine that MF portfolios does in fact yield greater risk-adjusted returns when compared to relevant benchmarks. An essential caveat to this is that different methodologies of measuring risk will greatly impact the conclusions about potential EMH violations (Chung et al. 2006). Moreover, due to the inherent variations in data set quality between reports, it is difficult to properly assess the degree to which the findings hold true.

1.1. Alpha and Beta

Alpha (α) is a term that reflects a specific investment strategy's efficacy. Moreover, this relates to both the Capital Asset Pricing Model (CAPM) and EMH. According to the EMH, it should not be possible to generate returns above average through utilizing historical financial data. CAPM, on the other hand, is a testable regression in which alpha is the intercept. In any case that there would be a violation against the EMH, the alpha is the appropriate measure of the extent of that violation. Thus, alpha is often used interchangeably with the terms "excess return" and "abnormal return". In normal cases, alpha approaches the value zero, thus there is no intercept nor any excess return. (Berk & DeMarzo 2017)

Beta (β) is often used in conjunction with alpha and also relates heavily to the CAPM. Beta should be thought of as a risk coefficient for the CAPM regression. This coefficient is often normalized to one which is the appropriate measure of the systematic market risk. When the beta of an asset or portfolio is equal to one, the return profile of that asset perfectly correlates with the market. However, as soon the beta assumes values greater or lesser than one, then the risk is either increased or decreased in comparison to the market. The consequences of a high beta (>1) are increased returns during bull markets, but also increased losses in bear markets. (Berk & DeMarzo 2017) As a point of reference, both alpha and beta are widely used within theoretical frameworks to calculate the expected returns of assets and their risk. These terms are crucial to this paper and more depth on these topics will be provided in subsequent chapters and sections. The mathematical definition of beta can be found in Appendix 2.

1.2. Purpose and Contribution

By using rigorous methods and high-quality data, this paper assumes the ambition of quantifying and analyzing the risk-adjusted returns of MF portfolios on the Stockholm Stock Exchange. While testing the MFI strategy in itself is a compelling field of study, we recognize the diminishing return to research and therefore adopt a different approach to the strategy. Once the benchmark returns have been established, we will deepen our scope to analyze if it is possible to assign an optimal set of weights to the ranks given to the two metrics. We do this in an attempt to increase the returns for the whole sample period, without jeopardizing alpha. We have not come across any theses which tests this specifically and therefore find it to be an interesting sub-topic of the MFI strategy. By employing different weights, we pit the value metric against the quality metric. Depending on our findings, we will hopefully be able to draw conclusions about the two metrics' respective dependability for predicting future stock performance and excess returns.

The purpose of this thesis is fourfold, namely:

I. To test whether MFI actually constitute an anomaly or not on the Stockholm Stock Exchange for a recent time-period.

II. To, within our framework, analyze whether the equally weighted combination of RoIC and EY is better than deviations from that strategy and by so doing, draw conclusions about the metrics' power of predictiveness for future returns.

III. To decrypt RoIC and EY as key metrics and provide a solid understanding of the risk and reward profiles of various combinations of value and quality portfolios.

IV. To see whether the strategy is effective over time.

1.3. Delimitations and Outline

First, we will limit our scope to the Stockholm Stock Exchange and for the period between 2004 and 2018. For one, we find this period to be sufficiently substantial for the return data to paint an accurate picture of the risks associated with employing the strategy in both economic up- and downturns. Other important delimitations for this thesis are the models used for quantifying alpha. Once portfolio returns are computed, they must be compared to the required return of the portfolios. This will be done using the Fama-French Three-Factor Model (FF3F) and the Carhart Four-Factor Model (C4FM). Our benchmark index will be the OMX Stockholm Gross Index (OMXSGI).

2. Previous Research and Theory

This segment covers the previous research on MFI and the theory behind fundamental investing. The aim with this chapter is to provide the reader with thorough knowledge of various strategies applied within portfolio management, different measures of risk, market efficiency, exploitation of anomalies, and definitions. The research presented below will also inform the reader that there is a high degree of internationality and intertemporal applicableness to the findings. Thus, the abnormal returns are not limited to a certain geographic market or period of time.

2.1. The Efficient Market Hypothesis

Eugene Fama orchestrated the Efficient Market Hypothesis in the 1960's. Briefly, the EMH asserts that the current state of the stock market is the product of all information available to the participants in that market. (Fama 1965) Consequently, it cannot be possible to beat the market using historical data. Together with the Miller-Modigliani Irrelevance Proposition and the Capital Asset Pricing Model, EMH is one of three quite similar approaches that has greatly shaped modern-day financial economics theory. However, these theories have been subjected to significant scrutiny over time and they are all grounded in the idea that perfect market assumptions are valid (Modigliani & Miller 1958; Sharpe 1964; Fama 1965). According to Golsbee et al. (2013), markets are under perfect competition when the following seven criteria are fulfilled:

A. Large Number of Buyers and Sellers
B. Product Homogeneity
C. Free Entry and Exit of Firms
D. Profit Maximization
E. No Government Regulation
F. Perfect Mobility of Factors of Production
G. Perfect Knowledge

While it is quite obvious that these assumptions in their collective form are ill-suited for today's rapidly changing market environment, it seems as though the EMH in its broadest sense hold true. This is also affirmed through evidence stating that very few market participants, including professionals and active funds, will beat the market. If historic data could be used to predict future stock returns, then surely investment professionals would be able to generate returns higher than those of passive index funds (Malkiel 2005). Fama (1970) formulated three different versions of the EMH, which are presented in the following subsections.

2.1.1. Weak-Form Efficiency

This form states that stock prices fully mirror the information available to the market in which they trade. This is not only true for the current time period but all previous periods as well. According to Fama, this implies that it is not possible to construct any trading strategies that generate abnormal returns by leveraging historic trading patterns. Excess profits associated with strategies such as technical analysis are thus fully associated with excess risk or pure luck.

2.1.2. Semi-Strong-Form Efficiency

The semi-strong form adds an extra assumption to the preceding form. It alleges that today's prices are not only the product of historic information about the stocks' performance, but also all available information about the companies' income statement and balance sheet items. In effect, strategies such as fundamental analysis cannot be employed to gain returns above average. This form is especially interesting for our thesis as we will partially examine the power of predictiveness for fundamental analysis.

2.1.3. Strong-Form Efficiency

The strongest form efficiency claims that information about a company known to any market participant (including CEOs and CFOs) will be fully reflected in the company's stock price. The only way that this could possibly be true is if insider-trading was legal, as this would then let proprietary information about the company influence the market.

2.2. The General View on Market Efficiency and Anomalies

Most financial and economic models relevant to this paper are based on the perception of perfect markets (Dardi 2012). As stated above, perfect markets are subjected to a large amount of constraints and are in practice a rare sight (Dasgupta 1981). An imperfect market arises when there is information asymmetry and when individual sellers and buyers can influence the production or price. The stock market can thus be regarded as an imperfect market, as traders do not have equal or impeccable knowledge regarding listed firms or financial products. It is worth mentioning that imperfect markets can also have detrimental effects on participant's welfare. For example, when very few sellers exist within a market and enjoy too much control, problems are bound to arise. It is these occurrences that generate divisive ideological views on market efficiency hypotheses.

One side argues that once a market deviate from the perfect competition model, it is justified for the government to intervene in order to increase efficiency in either distribution or production. These interventions could origin in the form of fiscal/monetary policy, market regulation or anti-trust laws. The other side will argue that the government should very rarely be granted intervention to correct imperfect markets. This side also reasons that the government itself is imperfect since it does not always possess the information or incentives to correctly interfere in a market. (Golsbee et al. 2013) Among criticists of the EMH are Warren Buffet (Buffet 1984). While there is evidence that the market will, by and large, follow the EMH, there is also documentations that proves the opposite to be true (McGroarty & Urquhart 2016). The following section will shine some light on the fact that the EMH is not absolute and that there are systematic ways to "cheat" the market.

2.2.1. Calendar Effects

Some alleged calendar-based anomalies are the January effect and the Weekend effect. The January Effect states that the first month of the year have systemically higher returns than all other months (Haug & Hirschey 2006). Moller and Zilca (2008) suggests that there are higher abnormal returns in the first half of January and lower abnormal returns in the second half. The conclusion is that these two abnormalities largely off-set each other, and compared to historical trends, the overall abnormal returns seem to remain constant. Moreover, Perez (2017) informs that the January effect still holds for more recent periods in some markets but seems to be decreasing on an overall global level. The Weekend effect (also known as the Monday effect) relates to the idea that returns on the initiating day of the week are substantially lower than the returns of the same stock on the forgoing Friday (French 1980). While this was potentially true many years ago (Wang et al. 1997), the Weekend effect has since been declared to no longer constitute an anomaly (Robins & Smith 2016).

2.2.2. Size Effects

One example of size anomalies is the Small-firm effect which proclaims that small companies outperforms large companies (Roll 1981). However, modern studies like Patel (2012) confirms that due to the increased and inherent riskiness of small-firm portfolios compared to large-firm portfolios, it is not possible to achieve abnormal returns on a risk-adjusted basis using this strategy.

2.2.3. Company-Specific Variable Effects

The last effect that we will discuss is the practice of leveraging various financial metrics in an attempt to forecast returns and achieve alpha. Such strategies include betting on companies with high dividend yield, high operating profitability, low P/E numbers, and high Book-to-Market (BtM) ratios (Filbeck & Visscher 2003; Jiao & Lilti 2017; Fama & French 2012; Chen & Zhang 1998). The semi-strong form of EMH does not acknowledge the possibility of higher-than-average returns using this approach to investing. Yet, studies like Fama and French (2012) present previous suggestions of the "value premium", i.e. higher average returns for value stocks (low P/E or high EY). The value premium and factor-based investing is central to this study. Another relevant effect is the returns relating to beta-strategies. Under the CAPM, high-beta stocks should bear the potential of greater returns than the market to compensate investors for assuming extra risk. Dimson et al. (2017) argues that value stocks are typically companies which suffers from financial distress. If this is true, then it is likely that value investing is an inherently risky strategy to pursue. Moreover, Garlappi and Yan (2011) confirms that high default probabilities are correlated with high equity betas. Thus, if value stocks are typically distressed and distressed firms have higher betas, then these stocks should yield higher returns in bull markets. However, Frazzini and Pedersen (2014) find contradictory results in that a high beta is associated with a low alpha and that value-investors such as Buffet typically invests in companies with a beta below one.

We hypothesize that the weighting methodologies which focuses excessively on EY should have higher average betas and returns than the RoIC portfolios. Interestingly, Sweden is the only country in the report by Frazzini and Pedersen (2014) where a long strategy composing low-beta stocks is associated with a substantial negative alpha. Naturally, the average return over the monthly risk-free rate is also negative. This implies that it has historically been more profitable to go long high-beta portfolios in Sweden, according to the report.

2.2.4. Summary of Anomalies

The cohesive trend for the above discussed (plausible) abnormalities appears to be a decline in their power. Schwert (2003) suggests that empirical findings can decrease the probability of abnormal returns. This relates to the last assumption for perfectly competitive markets, namely perfect knowledge. As more participants become aware of strategies that achieve higher-than-normal returns, the market will auto-adjust its pricing due to the increased demand for such products. Thus, as markets become more developed, it is natural that further findings will appear and thereby exhaust abnormal profit opportunities and strategies. Relating to the scope of this paper, we wonder whether Greenblatt's strategy has been subjected to the same trend.

2.3. Greenblatt and the Magic Formula

Wharton-schooled Joel Greenblatt is an American hedge-fund manager and author that has gained a considerable amount of coverage since releasing the divisive MFI strategy (Yahoo! Finance 2019). The guiding philosophy behind his investment strategy is short and simple and can be expressed along the lines of "buying good companies at bargain prices" (Reese & Forehand 2009). While there may be no surprise to the fact that such stocks can potentially produce great returns, the rub lies within successfully identifying the companies that meet the criteria. Greenblatt's systematic approach to stock-picking seem to consistently find these firms, and that is what makes the strategy so special. Analysts and investors around the world spend countless of hours making assumptions about future earnings and still can't beat the market on average (CNBC 2019). Meanwhile, Greenblatt's strategy focuses solely on what is already known and leaves almost no room for assumptions.

Value-investing is nothing new to the world, and there is a plethora of existing studies on the topic. Studies like Abarbanell and Bushee (1998) proved that fundamental value analyses based on metrics such as the P/E-ratio can be used as an information-provider regarding future returns. We believe that the combination of value metrics such as P/E and quality-oriented metrics like RoE, RoCE, and RoIC has great potential for increasing the returns. Therefore, before we dig deeper into the systemization of the strategy, we wish to present some definitions and discuss the two metrics employed in this strategy and their nearly synergy-like effect.

2.4. Discussions on Metrics

This section provides the necessary knowledge needed to comprehend the structure and content of the various accounting metrics that are used within the delimitations of this paper. We will hereafter commonly refer to EY as the “value metric” and RoIC as the “quality metric”.

A. Return on Invested Capital

$$\text{Return on Invested Capital} = \frac{\text{EBIT}}{\text{Invested Capital}} \tag{1}$$

Ignoring the possibility of earnings management, a high RoIC will typically signal a healthy business. More specifically, RoIC is an indicator of a firm’s efficiency in leveraging its Invested Capital. While there may be a disconnect between a company’s health and its stock performance in the short run, a firm’s profitability and efficiency will likely be picked up by the market over the longer term, and thus be mirrored in its share price. (Yahoo! Finance 2017)

> Leaving the question of price aside, the best business to own is one that over an extended period can employ large amounts of incremental capital at very high rates of return. (Warren Buffet, 1992)

B. EBIT

“Earnings before interest and taxes” or EBIT, is an income statement line which is commonly used in equity valuation. EBIT disregards the differences in leverage and tax between companies and is often referred to as operating profit. As debt levels and effective corporate tax rates are known to fluctuate heavily, EBIT serves a good metric for comparison purposes. (Yahoo! Finance 2019)

C. Invested Capital

The following deductions can be useful in order to understand Invested Capital:

$$\text{Invested Capital} = \text{Net Working Capital} + \text{Net Fixed Assets} \tag{2}$$

where

$$\text{Net Working Capital} = \text{Current Assets} - \text{Current Liabilities} \tag{3}$$

$$\text{Net Fixed Assets} = \text{Assets} - \text{Current Assets} - \text{Intangibles and Goodwill} \tag{4}$$

Invested Capital is an accounting metric that combines capital infused by equity holders and creditors. It strips out assets that are formed in the business, i.e. working capital (including cash). Return on Invested Capital is therefore a profitability measure which measures the company’s efficiency in generating operating income using capital provided by investors. The reason RoIC is favored over other profitability metrics such as RoE and RoA is that we want to disregard capital items that are not specifically crucial to the continuation of the business. By using RoIC, we strip out items like goodwill and other intangibles and focus exclusively on the core capital within firms. (Berk & DeMarzo 2017)

D. Earnings Yield

$$\text{Earnings Yield} = \frac{\text{EBIT}}{\text{Enterprise Value}} \tag{5}$$

EY is similar to the more commonly used P/E-ratio and both of them are classified as valuation metrics. Nonetheless, while P/E is the ratio between the Equity Value (EqV) and Net Income, EY measures the relationship between EBIT and Enterprise Value (EV). The important difference is that enterprise value includes net debt since EBIT is based on income distributable to both equity and debt holders. Another important note is that EY reverses the P/E equation. While a high P/E-ratio indicate that the company is overvalued in relation to its accounting earnings, a high EY signals an undervalued stock. When the company can recoup a significant amount of its EV with one year's operating profit, it is assumed that the company is relatively cheap to buy. (Yahoo! Finance 2014)

We find two main intuitive motivations that supports the combination of RoIC and EY. Firstly, the quality metric provides credible insight into the business' efficiency in generating profit. Secondly, the value metric indicates whether the stock itself has potential to increase in price. Although there are some caveats to this reasoning, buying into firms with a high RoIC and a high EY should in theory be a good idea. However, simply investing in undervalued stocks might not be a good strategy as the undervaluation itself could be caused by financial difficulties and impaired prospects for future earnings. Similarly, focusing solely on the quality metric might also lead to underperforming portfolios. Thus, we believe that there is power in the combination of these metrics. However, we also wish to test this belief by employing our weighting system. By analyzing the different returns, we can hopefully arrive at an optimal weighting solution and also conclude which of these metrics are most powerful for predicting future returns.

2.5. The Magic Formula Ranking System and Weighting

As previously mentioned, the first part of the formula is to rank-order stocks based on RoIC and EY separately. Below is an initial example of how the ranking works, including the calculation of the total rank. The original strategy places equal emphasis on RoIC and EY. It is a company's total rank that matters when producing the portfolios. (Greenblatt 2006) We use the rank formula instead of averaging the two metric scores, as we want the screening to find firms which are well positioned within both metrics. If one would average the two metrics, a firm with an extremely high or an extremely low RoIC/EY could potentially find its way into the portfolios. However, such a firm would typically not be aligned with what Greenblatt aimed at achieving with his investment strategy. If that would happen, we would then be compromised in our ability to draw relevant conclusions regarding the result. Moreover, the ranking system proves to be very useful for the purpose of weighting, which is at the absolute core of this study. Figure 1 exemplifies the workings of the original ranking system.

	RoIC	EY	Total
Stock "A"	2	4	6
Stock "B"	1	6	7
Stock "C"	3	8	11
Stock "D"	5	7	12
Stock "E"	8	5	13

Figure 1 A Demonstration of the Original Ranking System

In this paper, we will distinguish ourselves from previous research by simulating the effects on the total return for each portfolio by assigning different weights to the two metrics. This methodology will create the possibility of an additional 20 portfolios for each year in our sample. Figure 2 demonstrates how we structure the weighting combinations.

RoIC	EY
100%	100%
100%	90%
100%	80%
100%	70%
100%	60%
100%	50%
100%	40%
100%	30%
100%	20%
100%	10%
100%	0%

To the left; holding the discount parameter of RoIC constant at 100% while simulating different weights to the value assigned to the EY component.

To the right; holding the discount parameter of EY constant at 100% while simulating different weights to the value assigned to the RoIC component.

RoIC	EY
100%	100%
90%	100%
80%	100%
70%	100%
60%	100%
50%	100%
40%	100%
30%	100%
20%	100%
10%	100%
0%	100%

Figure 2 Our Weighting System

Although trivial, this weighting system serves as an easily wielded framework for managing risk and return. In line with Dimson et al. (2017), we hypothesize that increasing the emphasis on EY will increase the likelihood of incorporating distressed assets in our portfolios. That being said, the probability of higher returns is greater, but so is the probability of losses. If the analogy that value firms have higher betas is correct as well, then we are likely to end up with a framework that allows for risk steering. Investors could potentially use the framework to increase or decrease risk by weighting towards the most preferable solution. To test whether this is true, we will need to find out the actual beta profiles of the RoIC and EY portfolios, respectively.

2.6. Risks Associated with our Test

As with all tests, there are certain risks which can result in erroneous conclusions. In this section, we will discuss relevant biases that could potentially contribute to wrongful data results.

2.6.1. Survivorship Bias

When excluding defaulted or delisted assets, analysts are at risk for survivorship bias (Brown et al. 1992). This might lead to invalid conclusions as potential downside is stripped out of the portfolios examined. We will avoid this problem by including all companies that have been listed on the Stockholm Stock Exchange at one point in time since January 2004. Nonetheless, if a company included in one of our portfolios is declared bankrupt or delisted, the portfolio will immediately bear the loss of that bankruptcy and its effect will then be included in our return results. However, this is likely to be a rare occurrence.

2.6.2. Look-Ahead Bias

Look-ahead bias is a potential risk that specifically relates to back-testing. A basic mistake is to include data that would not have been accessible to investors at the testable time-period. This is then referred to as look-ahead bias. (CFA 2018) We avoid this type of bias completely by only using variables known at each point in time as the test is progressed.

2.6.3. Time-Period Bias

Problems relating to time-biases can occur when the data sample excludes time-periods of macroeconomic distress or similar events (CFA 2018). For example, a researcher might benefit from excluding returns during financial crises to increase the total return for the period return. We aim to extend our sample sufficiently in order to include effects from both economic contractions and expansions on the strategies pursued.

2.6.4. Other Risks

One potential caveat for our test is that increased EY weighting might serve as a proxy for greater risk. Consequently, when increasing the weighting towards the EY component, we might very well raise the inherent risk-level within the portfolio. If this is the case, and if the total return is not sufficiently high in comparison to the risk, then the alpha of the EY portfolios should be inexistent.

2.7. Previous Reports Back-Testing Magic Formula Investing

Due to the straightforwardness of the strategy and the seemingly anomalous returns, Greenblatt's strategy has been subjected to a lot of scrutiny and analysis. This segment aims to analyze previous studies back-testing the MFI and also discuss the notable features that has been used in order to tweak the returns of the strategy.

2.7.1. Article 1 – Finnish Market

Davydov et al. (2016) compares MFI to other value investing strategies on the Finnish market for the years 1991-2013. Some of the comparable strategies include pure value investing such as betting on Earnings to Price (E/P) and EBIT/EV. Quite interestingly, the study employs an augmented version of the MF called MF-CF. This strategy adds a Cash Flow to Price (CF/P) ratio to the ranking system. CF (operating cash flow) is defined as "*the sum of net income and non-cash charges or credits that include depreciation and amortization items plus income statement deferred taxes*", according to the paper. When dividing CF with the price of equity (P), a value ratio is rendered. This ratio measures the degree to which the equity value can be earnt by means of one year's operating cash flow. The purpose of this is to allow space for companies which are CF-positive but suffer from losses related to accounting items such as depreciation and other non-cash charges.

While the paper find that all strategies yields higher return than the market (for all years in the sample), the EV/EBIT strategy is highlighted for realizing the highest alpha. Risk-adjusted returns are computed using CAPM and the C4FM. Carhart's alpha amounts to 6.71%, 7.66%, and 7.58% for the MF, MF-CF, and EV/EBIT strategies, respectively. These findings are statistically significant at the 5% level, according to the authors. (Davydov et al. 2016)

2.7.2. Article 2 – Nordic Market

This article by Persson and Selander (2009) test MFI on the Nordic market (Sweden, Norway, Denmark, Finland, and Iceland) for the years between 1998 and 2007. The method used differentiates from the traditional model as they rebalance the portfolio every month, using the ranking system. Moreover, they test an allegedly "optimized" version focusing on Return on Capital Employed (RoCE). The authors hypothesize that the RoCE portfolio (Portfolio II) will generate greater returns over the traditional portfolios (Portfolio I). Their rationale is that a larger capital base should provide a more accurate depiction on the companies' efficiency in generating operating profit. Indeed, they find that Portfolio II (CAGR 26.01%) generates higher returns than Portfolio I (CAGR 14.68%). However, the authors simply attribute this to greater risk and refers to a standard deviation of 10.40% versus 5.92% for Portfolio II and Portfolio I, respectively. Moreover, the authors conclude that the alphas generated are not statistically significant and therefore reject the hypothesis that MFI constitutes a market anomaly. A reason for this conclusion could be that they use American factors (downloaded from Kenneth R. French's database) to run the FF3F regression on Nordic stocks. The main risk-measures used are standard deviation, Sharpe ratios, CAPM, and FF3F.

2.7.3. Article 3 – World Market

Blackburn and Cakici (2017) from Fordham University study the returns from a factor-based investment approach. The factor is constructed by long positions in high (low) RoIC (EY) firms and short positions in low (high) RoIC (EY) firms. They call this a PV-UG strategy, which is an acronym for "profitability and value versus unprofitability and growth". The study has a global focus for the sample period 1991-2016 and employs FF3F, CF4F, and CAPM for factor loading. They also compare portfolios where RoIC is numerated by Gross Profit (GP) to the normal portfolios (with EBIT-numerated RoIC). They find that portfolios in which RoIC is numerated by GP achieves greater returns. They explain this by reasoning that GP is a less "contaminated" measure of profitability. According to the authors, the abnormal rate of returns amasses to 1.19%, 0.45%, 0.52%, and 0.82% for the North American, European, Japanese, and Asian market, respectively. This is calculated using the C4FM. Only the European market's alpha is found to be significant (at the 5% level).

2.7.4. Article 4 – South-African Market

Lambrechts and Roos (2017) studies a spin-off on Greenblatt's strategy based on RoA and P/E ratios on the Johannesburg Stock Exchange for the period between 2006 and 2013. The authors compare the returns from a variety of different portfolios sorted after size and holding period. They find that portfolios with a holding period of one year and a size of 10 yield the greatest average annual returns (18.26%) while portfolios with a size of 50 and a holding period of two years yield the lowest returns (12.80%). For all holding periods, the average annual return decreases as the portfolio sample size increases. The primary risk model applied in their test is the FF3F and the authors find statistically significant alphas (with p-values ranging from 1% to 10%) for almost 80% of the portfolios (15 out of 19).

2.7.5. Article 5 – Brazilian Market

As opposed to the other articles we have discussed so far, Gunnar & De Paula (2016) focuses solely on the traditional magic formula for the 2006-2015 period. The test involves rebalancing portfolios every 6th and 12th month and finds that 12-month portfolio holdings generate higher returns over the 6-month portfolios. When assessing the alpha, the study cannot find statistical significance at any relevant p-value.

2.7.6. Summary of Previous Studies

Most of the articles presented in this literature review confirms that MFI substantially outperform relevant benchmark indices and produce excess returns in relation to the risk assumed. However, since some of the results are incoherent in relation to the extent of the alpha and its statistical significance, we wish to establish this ourselves. Another interesting finding is that many of these articles try to augment the magic formula in order to achieve higher returns than the traditional model. In general, the augmentation processes involve alternating between different profitability measures or adding some new component, such as cash flow, to enhance the overall quality of the stocks included. Finally, Lambrecths and Roos' findings are important for our test and by drawing from their results, we find insight in that rolling 12-month portfolios consisting of up to 20 stocks should be suitable for spawning sound returns.

Literature Review Key Point Summary

Article name	Magic Formula vs. Traditional Value Investment Strategies in the Finnish Stock Market	Back Testing "Magic Formula" on the Nordic Region	The Magic Formula: Value, Profitability, and the Cross Section of Global Stock Returns	Applying Joel Greenblatt's Value Investment Strategy to the Johannesburg Stock Exchange	Backtesting the Magic Formula on the Brazilian Stock Market
Author(s)	Davydov et al	Persson and Selander	Blackburn and Cakici	Lambrecht and Roos	Gunnar and de Paula
Year	2016	2009	2017	2017	2016
Publisher	Nordic Journal of Business	Stockholm School of Economics	Fordham University	Management Dynamics	University of Gothenburg
Market(s)	Finnish	Nordic	North America, Asia, Europe	South-African	Brazilian
Tests made	E/P, EV/EBIT, MF-CF, MF	MF I (RoIC), MF II (RoCE)	MF, GP-numerated RoIC	MF (RoA, P/E)	MF
Period	1991-2013	1998-2007	1991-2016	1996-2013	2006-2015
Risk measures	Sharpe, CAPM, C4FM	Sharpe, CAPM, C4FM, SD	CAPM, FF3F, C4FM	Sharpe, FF3F	Beta, FF3F
Significant Alpha?	Yes	No	Partly	Yes	Partly

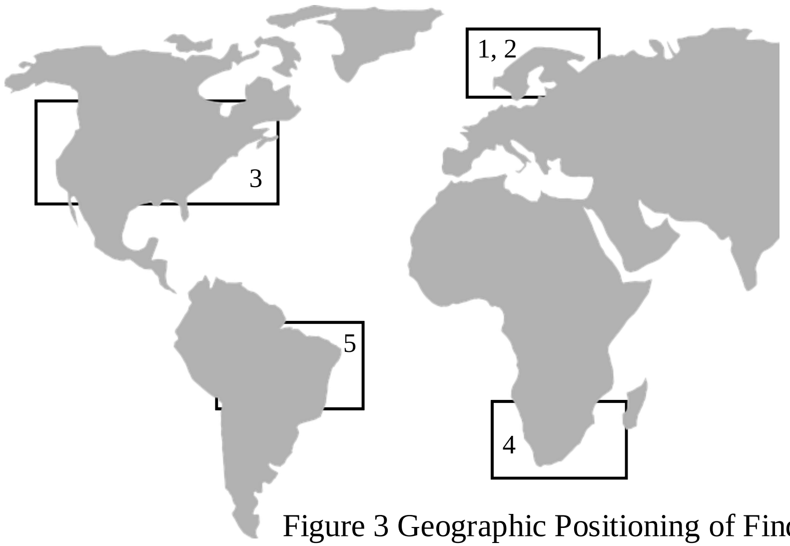

Figure 3 Geographic Positioning of Findings

Notes to Findings in Previous Literature:

- Common risk measures are the CAPM, FF3F, and C4FM. Alpha is found in most of the reports, at least to some extent.
- Sample periods ranges between 10 and 15 years.
- The strategy seems to be effective over time and across regions.
- Large variations in terms of augmentation.

2.8. Quantification of Benchmark Risk

The two risk models that we will employ in our study are the Fama-French Three-Factor Model and the Carhart Four-Factor Model. Similar to any other models for measuring risk, these two are strongly grounded in the notion that it is not possible to realize gains above and beyond what the level of risk warrants. It is important to remember that any strategy that outperforms large indices or achieves similar stellar returns can potentially be fully explained by risk factors. Simply put, high returns may be caused by nothing other than greater risk, which is perfectly natural. This chapter sets out to explain the different models that can be used to draw conclusions about risk-adjusted returns.

The models that will be used in this paper are further developments of the Capital Asset Pricing Model. The CAPM was developed by William Sharpe (1964) and is expressed as follows:

$$r_i = r_f + \beta_i(r_{MKT} - r_f) \tag{6}$$

The components include the risk-free rate of return, the market rate of return, and the asset beta. The only variable that differs between assets in a market is the beta value. Thus, within the CAPM framework, this coefficient explains the expected rate of return of the asset. Like all of the succeeding equations, CAPM can be transformed into a testable regression model, denoted as:

$$r_{i,t} - r_{f_t} = a_i^J + \beta_i\left(r_{MKT_t} - r_{f_t}\right) + \epsilon_{i,t} \tag{7}$$

The regression calculates the return of the asset in excess of the monthly risk-free rate as a function of adding alpha to the beta times the market premium. Epsilon is an error term. In any case the model fails to predict the actual return, an intercept (alpha) is created. Market participants who can generate portfolio returns with significant alphas are said to have predictive capabilities. Although the CAPM laid the foundation for many risk models to come, it is quite incomplete.

2.8.1. Risk model 1 – Fama-French Three-Factor Model

Eugene F. Fama and Kenneth R. French (1993) extended the CAPM to include SMB and HML in their Three-Factor Model (F3FF). SMB (‘Small minus Big’) is a monthly factor that can explain the return effects from buying small firms and shorting large firms. Similarly, HML (‘High minus Low’) explains the effect from buying stocks with a high Book-to-Market (BtM) value and shorting stocks with a low BtM. Respectively, these factors try to eradicate positive alphas by controlling for the “size effect” and “value effect” which are two market anomalies previously discussed in this paper. The testable regression of the Fama-French Three-Factor Model is expressed below:

$$r_{i,t} - r_{f_t} = a_i^{FF} + \beta_i\left(r_{MKT_t} - r_{f_t}\right) + s_i(SMB_t) + h_i(HML_t) + \epsilon_{i,t} \tag{8}$$

2.8.2. Risk model 2 – Carhart Four-Factor Model

Mark Carhart (1997) extended the Fama-French Three-Factor model by including an additional factor, named momentum (MOM). Momentum is also called 'Winners minus Losers' and is consequently the return from long and short positions in stocks with the highest and lowest preceding 12-month returns. As a regression, the C4FM model takes the following form:

$$r_{i,t} - r_{f_t} = a_i^C + \beta_i\left(r_{MKT_t} - r_{f_t}\right) + s_i(SMB_t) + h_i(HML_t) + m_i(MOM_t) + \epsilon_{i,t} \qquad (9)$$

Over time, new models have been constructed, for example the Fama-French Five-Factor Model (2014), which included CMA (Conservative minus Aggressive) and RMW (Robust minus Weak). These factors try to address the returns that stem from betting on firms with aggressive investment strategies (CapEx) and high operating profitability, respectively. The latter could potentially be a good explanatory variable for our portfolio returns, as there is a strong presence of quality and profitability in the stocks. To conclude, FF3F and C4FM has been included in our study because we find them suitable for the kind of test that we are performing. Although we would have liked to incorporate the FF5F, this was not possible due to data limitations.

2.8.3. Summary of Risk Modelling

The rationale behind the concept of adding extra factors is to further explain returns. For example, of all the models that has been presented in this chapter, only the FF5F controls for "quality". That being said, it is quite probable that the Magic Formula does not generate significant alphas when tested against the F5FF. This is precisely due to quality being an integral part of the core metrics in the study. This might also explain why no previous study has extended the test to include more than four factors.

3. Methodology and Data

3.1. Research Questions

This paper aspires to answer the following questions in relation to the MFI:

I. Using a systematic weighting approach to RoIC and EY, is it possible to find an optimal solution for producing abnormal returns?

II. How does RoIC and EY differ from other similar value and profitability metrics?

III. How does the weighting affect the risk profile of the portfolios?

We do not believe that it is possible to achieve greater risk-adjusted returns by deviating from the traditional magic formula strategy, i.e. weighting RoIC and EY equally. However, we aspire to test this empirically. The hypotheses formulations in relation to the research questions follows:

H1: It is not possible to increase the returns without increasing risk using a systematic approach to the weighting framework.

H2: RoIC and EY does not differ from similar metrics in their ability to predict future returns.

H3: The risk profile of the portfolios remains unchanged as the weighting combinations are altered.

3.2. Databases

The data that has been used for testing the hypotheses has been downloaded from Bloomberg Terminal's and FactSet's databases. To be able to perform the test, we primarily need the stock price at the beginning of each month between 2004 and 2018. By leveraging these data points, we can calculate the monthly returns for the assets included in the study. Moreover, we use Total Return (TR), which includes dividend. Thus, the calculations using TR represents the absolute gains the shareholder will receive over the year. Bloomberg Terminal is the most used data provider within the finance sector and thus the go-to toolbox for professional investors all around the world. FactSet is another database, similar to Bloomberg Terminals, but not as powerful. As both of these terminals are used by actual investors who invest and manage billions every year, one can be confident in that these databases have trusted returns, earnings, and balance sheet data. (Bloomberg 2019; FactSet 2019)

Fama-French factors have been downloaded from the Swedish House of Finance's database for the years 2004-2016. Unfortunately, we could not receive factor data beyond 2016. We will therefore not be able to calculate the risk-adjusted returns past 2016. We use monthly frequency and equally weighted factors to match the profile of our generated portfolios. To obtain the equity beta values of stocks, we have used Yahoo! Finance and in some instances Avanza Bank, as neither had betas for all firms. Furthermore, OMXSGI data has been downloaded from Nasdaq Nordic.

3.3. Total Return

Using Bloomberg and FactSet, we downloaded data for all firms that were listed at the beginning of each year on the Stockholm Stock Exchange between 2004 and 2018. We then downloaded the firms' RoIC at the end of each year for the time period 2003 to 2018, and EBIT for the same time period as well. We also calculated the applicable enterprise value (EV) at the beginning of each year. Having this information, we could then calculate the metric EY. Finally, we also downloaded the TR for each stock and for each month in addition to the total yearly return. The TR was calculated as:

$$\mathrm{TR_t} = \frac{\mathrm{Price_t} - \mathrm{Price_{t-1}} + \mathrm{Dividend}}{\mathrm{Price_{t-1}}} \qquad (10)$$

3.4. Building our Portfolios

We had to refine the dataset by excluding companies within the financial sector. This was done due to the fact that the metric RoIC cannot typically be applied to these firms. Once we received our new dataset, we ranked the firms for each year on both RoIC and EY. The firm with the highest RoIC for a specific year received the score of 1 and the firm with the second highest RoIC received a 2, and so on. This meant that the top firm would have the lowest rank and the worst got the highest. The same method was then used for ranking each company on their EY as well. We then aggregated each firm's metric score to calculate the total score for each year. In the original strategy, the lowest theoretical score a firm could receive was 2. As we downplay the emphasis on one of the two metrics, the lowest theoretical score decreases as well. The purpose of this screening was to see which firms to invest in. We also made it possible to weigh the metrics RoIC and EY. This was done by multiplying each metric by a coefficient. In the base case the constants were equal to 1, see the formula below:

$$\text{Total score}_\mathrm{t} = \gamma * \mathrm{RoIC_t} + \theta * \mathrm{EY_t} \qquad (11)$$

$$\text{where } 0 \leq \gamma \leq 1 \text{ and } 0 \leq \theta \leq 1$$

The 20 firms with the lowest total score were then chosen and placed in our portfolio for each specific year. These receive a portfolio weight of 1/N, i.e. 5%. To speed up the process we built Macros in Excel for each year which were coded to quickly rank and add the firms into each yearly portfolio. We then assigned the monthly TR, which we had already calculated, for each of the stocks in the portfolio. Doing this we could observe how the investments performed during each year and also compare their performance with OMXSGI. The last step was to summarize each year's performance in order to analyze the total performance over the 15 years and compare it to OMXSGI's development.

Next, we wanted to observe how changing the weights of the metrics would change our returns. Thus, we changed one of the metric's coefficient by 0.1 at a time in the interval of $0 \leq \gamma \leq 1$, while keeping the weight for the other metric's coefficient at one, $\theta = 1$. We always kept one of the coefficients equal to one as the difference between for example $\gamma = 0.8,\ \theta = 0.9$ and $\gamma = 0.8,\ \theta = 1$ is negligible. We continued with the opposite methodology of keeping gamma constant and changing theta. All in all, we created the possibility of 21 different portfolios with the different set of weights.

3.5. In-sample Test

To test which systematic weighting methodology of the metric's coefficients provide the best return, we constructed an in-sample test. Thus, when we had calculated the TR of each weight, we divided the 15-year horizon into two investment periods. The first part consisted of the first seven years, from 2004 to 2010, and the second part was the remaining eight years between 2011 and 2018. We then calculated the average TR for the first period as well as the second period. Having these two new data points, one could then easily compare the TRs between the differently weighted portfolios over two time-intervals. If the same weighting methodology has the highest returns in both periods, then that weighting can be declared most dependable. If we only look at the final years accumulated return, we risk making erroneous conclusions. This is because a strategy could easily outperform during a few years but not be the most systematically powerful combination over time.

3.6. Testing Portfolio Returns Against Fama-French and Carhart

In order to see if we could generate positive alpha with our portfolios, we needed to run a Fama-French as well as a Carhart test, i.e. the F3FF and C4FM. As these tests requires monthly returns, we had to calculate the monthly TR for each of the 20 stocks in each annual portfolio. We then used the average of the 20 stocks for each month in order to calculate the monthly TR of the portfolio. Thus, we could then easily calculate the required monthly excess return, which is defined as monthly TR of our portfolio subtracted by the monthly risk-free rate, $r_i - r_f$. The next step was to perform a regression analysis, which we did by using Excel's Data Analysis Tool. The y input range was the monthly excess return for each month between 2004 and 2016, while the x range was the Fama-French/Carhart's factors for the same time period. This gave us the alpha as well as the p-value, which helped us to evaluate the investment strategy and analyze whether our strategy generated alpha. This was done for each of the 21 differently weighted portfolios.

4. Findings and Results

In this section, we aim to clearly explain the results that has been established through our data model. The simulation of our portfolios yields interesting data.

Question I: *Using a systematic weighting approach to RoIC and EY, is it possible to find an optimal solution for producing abnormal returns?*

By observing Figures 4, 5, and 6, one can clearly see that the weighting methodologies effectively establishes different outcomes. Figures 4, 5, and 6 compiles the worst performing weighting strategy, the best performing weighting strategy, and the weighting strategy that normalizes both RoIC and EY to 1. The base case produces a total holding-period return of 1,420% whereas OMXSGI returns 346% for the period between 2004 and 2018. These returns have been calculated as the final years invested amount divided with an initial amount of 100,000 SEK invested at the end of year 2003. All amounts are continuously compounded as the test does not allow for any money to be withdrawn from the portfolio over the investing horizon.

ROIC	**EY**							
1	**1**	(End of year)						
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Performance	100 000	135 770	228 075	308 114	296 698	180 395	347 041	423 248
Return MFI		35,77%	67,99%	35,09%	-3,71%	-39,20%	92,38%	21,96%
Return OMX30		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%
						Avg. return/year 2004-2010, MFI		30,04%
						Avg. return/year 2004-2010, OMX		0,17%
	2011	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
	485 864	576 688	705 125	812 981	1 185 793	1 678 115	1 694 747	1 520 122
	14,79%	18,69%	22,27%	15,30%	45,86%	41,52%	0,99%	-10,30%
	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
						Avg. return/year 2011-2018, MFI		18,64%
						Avg. return/year 2011-2018, OMX		0,09%

Figure 4 Weighting set to 1:1

The worst holding-period return can be observed in the portfolio which has the RoIC weight set as 1 and the EY weight set as 0.2, which means that the investors almost solely invest in firms based on their RoIC rank. This strategy produces a return of 1,022%, which is far better than the OMXSGI return but still worse than our base case.

ROIC	EY							
1	0,2	(End of year)						
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Performance	100 000	127 592	199 962	258 912	241 829	156 130	293 732	346 131
Return MFI		27,59%	56,72%	29,48%	-6,60%	-35,44%	88,13%	17,84%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%
						Avg. return/year 2004-2010, MFI		25,39%
						Avg. return/year 2004-2010, OMX		16,89%
	2011	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
	369 205	403 282	458 202	598 039	925 862	1 240 891	1 252 503	1 122 148
	6,67%	9,23%	13,62%	30,52%	54,82%	34,03%	0,94%	-10,41%
	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
						Avg. return/year 2011-2018, MFI		17,43%
						Avg. return/year 2011-2018, OMX		8,71%

Figure 5 Weighting set to 1:0.2

The weighting combination that outperform the other portfolios is when the metrics are given the weights RoIC equal to 0.1 and EY equal to 1. This investing strategy yields an astonishing return of 2,223%. This is more than two times as much as the worst strategy and nearly six and a half times better than the OMXSGI. Furthermore, an interesting observation is that the EY-focused portfolios generate overall better returns in the first time period, between 2004 and 2010 than the RoIC-focused portfolios. However, in the second time period between 2011 and 2018, the opposite is true. This can be observed in Appendix 4. where we have included the performance of all the 21 portfolios.

ROIC	EY							
0,1	1							
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Performance	100 000	141 330	233 679	345 766	301 917	177 056	411 430	555 407
Return MFI		41,33%	65,34%	47,97%	-12,68%	-41,36%	132,37%	34,99%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%
						Avg. return/year 2004-2010, MFI		38,28%
						Avg. return/year 2004-2010, OMX		16,89%
	2011	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
	619 604	714 621	943 708	1 069 741	1 503 086	2 023 570	2 379 830	2 323 060
	11,56%	15,34%	32,06%	13,36%	40,51%	34,63%	17,61%	-2,39%
	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
						Avg. return/year 2011-2018, MFI		20,33%
						Avg. return/year 2011-2018, OMX		8,71%

Figure 6 Weighting set to 0.1:1

An observation that will be discussed more thoroughly in our last section is that the returns systematically increase as the emphasis on the EY component is toned up. The opposite is true when more emphasis is put on the RoIC component. Thus, we can conclude that EY is a better metric than RoIC for predicting returns. In Figure 7, the yellow line represents the best performing strategy with the RoIC-weight set to 0.1 and EY set to 1. Another observation which can be made is that the strategies with more weight toward EY also experience larger declines than their counterparts. This can easily be observed in the

2008, 2011 and 2018 decline. To visualize more clearly, the graph below lots the returns from the two best portfolios, the two worst portfolios, the original MFI portfolio, and the OMXSGI[1].

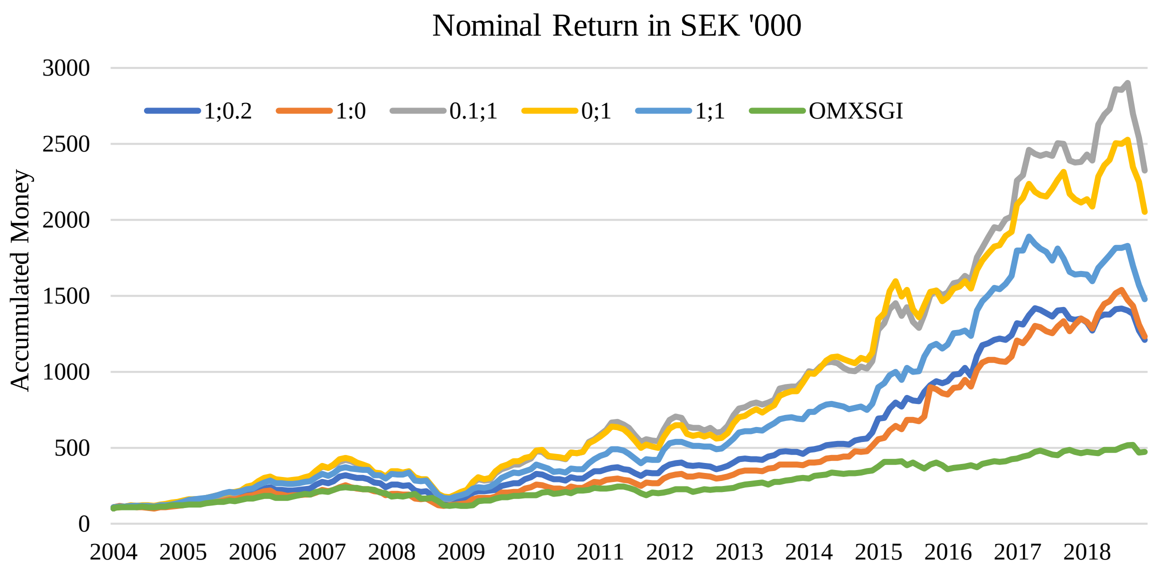

Figure 7 Nominal Return Comparison

Figure 8 plots our yearly return data. It shows the yearly returns from the original MFI strategy against the OMXSGI. For almost every year, the MFI returns are higher than the index.

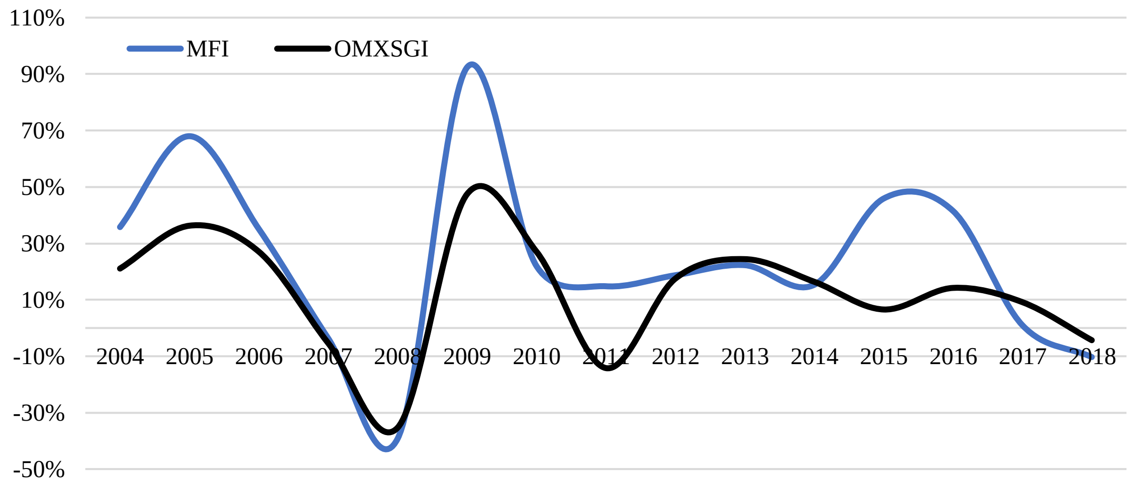

Figure 8 MFI vs. OMXSGI

Figure 9 and 10 plots the yearly returns for all possible weighting combinations. We conclude that the peak and average returns are higher for portfolios focusing more on value.

[1] Note that the OMXSGI is the value-weighted Stockholm All-Share Index with reinvested dividends.

However, these portfolios also seem more susceptible to down-side risk. This finding is in line with our theorization of value and risk.

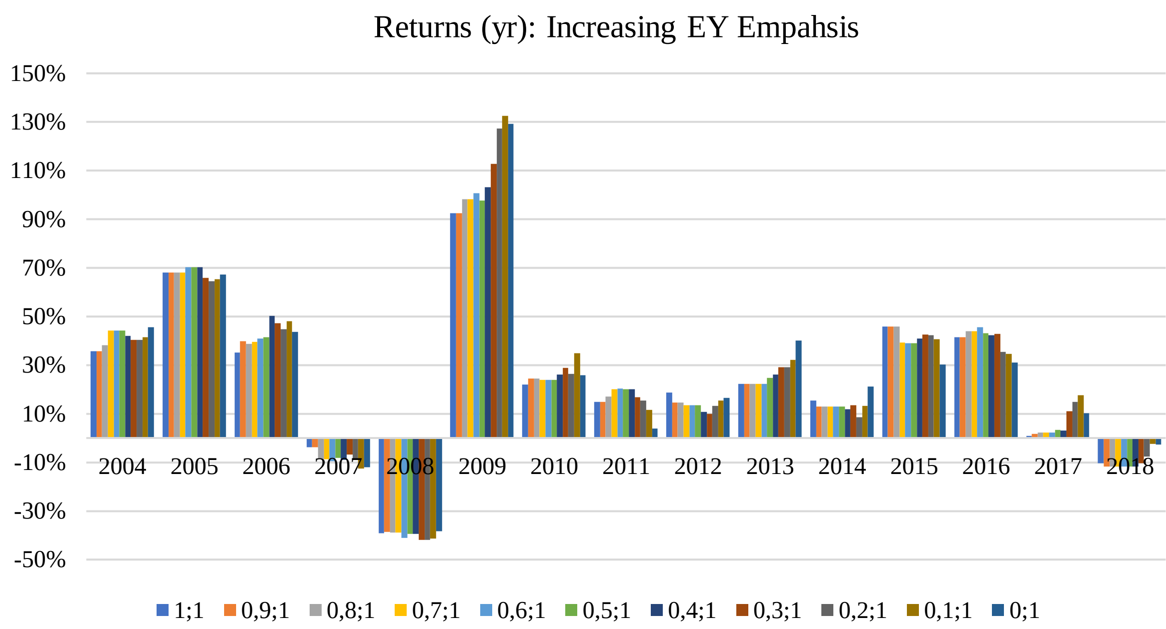

Figure 9 Portfolio Yearly TR with Increasing EY Emphasis

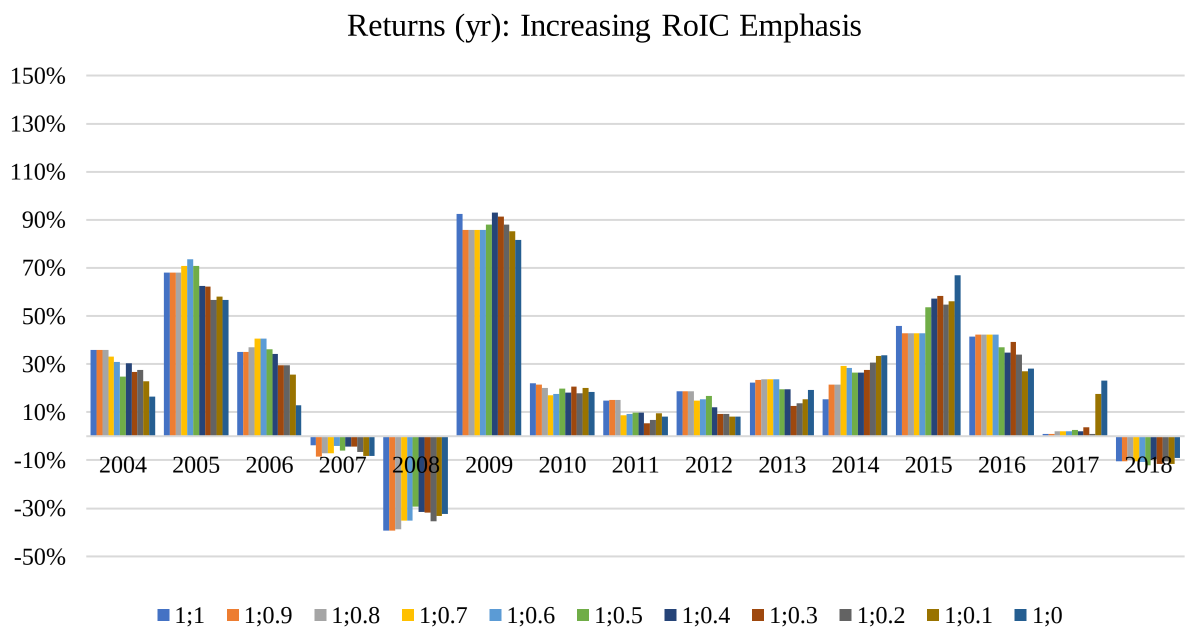

Figure 10 Portfolio Yearly TR with Increasing RoIC Emphasis

To finally answer the first and main question of this study, we created two tables that show the alphas generated from regressions against the three and four factor models. We can clearly see that the alphas are positive, although small, for all of our portfolios and weights. Adding to this, there is a high degree of statistical significance in our findings. This is true for the F3FF as well as the C4FM. The intercepts are systematically increased as the portfolio emphasizes more on EY. The opposite is true for the RoIC portfolios.

RoIC:EY	3 Factor Alpha	P-value*	RoIC:EY	3 Factor Alpha	P-value*
1:1	1,466%	0,00057	1:1	1,466%	0,00057
1:0.9	1,434%	0,00068	0.9:1	1,465%	0,00063
1:0.8	1,446%	0,00060	0.8:1	1,473%	0,00061
1:0.7	1,480%	0,00049	0.7:1	1,476%	0,00064
1:0.6	1,503%	0,00035	0.6:1	1,485%	0,00081
1:0.5	1,535%	0,00013	0.5:1	1,508%	0,00057
1:0.4	1,535%	0,00013	0.4:1	1,532%	0,00057
1:0.3	1,535%	0,00013	0.3:1	1,530%	0,00069
1:0.2	1,314%	0,00116	0.2:1	1,490%	0,00156
1:0.1	1,285%	0,00114	0.1:1	1,522%	0,00115
1:0	1,203%	0,00459	0:1	1,485%	0,00129

Figure 11 Three Factor Analysis for 2004-2016, *Indicates P-value at 95% Confidence Level

RoIC:EY	4 Factor Alpha	P-value*	RoIC:EY	4 Factor Alpha	P-value*
1:1	1,467%	0,00065	1:1	1,467%	0,00065
1:0.9	1,427%	0,00081	0.9:1	1,459%	0,00076
1:0.8	1,445%	0,00069	0.8:1	1,476%	0,00069
1:0.7	1,483%	0,00055	0.7:1	1,472%	0,00076
1:0.6	1,508%	0,00038	0.6:1	1,480%	0,00097
1:0.5	1,547%	0,00014	0.5:1	1,496%	0,00072
1:0.4	1,547%	0,00014	0.4:1	1,542%	0,00061
1:0.3	1,384%	0,00079	0.3:1	1,537%	0,00075
1:0.2	1,288%	0,00160	0.2:1	1,503%	0,00160
1:0.1	1,262%	0,00157	0.1:1	1,552%	0,00104
1:0	1,201%	0,00511	0:1	1,511%	0,00120

Figure 12 Four Factor Analysis for 2004-2016, *Indicates P-value at 95% Confidence Level

Question II: *How does RoIC and EY differ from other similar value and profitability metrics?*

To answer our second research question, we constructed low PtB portfolios to test whether the returns would be similar to our EY portfolios. PtB is the reciprocal of the Book to Market ratio (BtM), which is what Fama and French used to construct their HML factor. We then argue that if there is a difference in predictability between the two metrics, the output from the regression against the F3FF or C4FM should not be the same. We did the same for the high EBIT % portfolios, although profitability and quality is not directly captured by any of our models. It is clear that the PtB strategy is not a profitable one. On the other hand, the EBIT% strategy is, and its alpha closely resembles the RoIC portfolios' alphas.

PtB Strategy	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Alpha	-1,638%	0,607%	-2,69936	0,00774
RMKT-RF	57,424%	12,877%	4,45938	0,00002
SMB	15,279%	11,412%	1,33879	0,18265
HML	-13,320%	20,076%	-0,66347	0,50804
MOM	-15,312%	15,718%	-0,97422	0,33151

Figure 13 PtB Strategy - Regression Output

EBIT% Strategy	*Coefficients*	*Standard Error*	*t Stat*	*P-value*
Alpha	1,290%	0,438%	2,94783	0,00371
RMKT-RF	29,511%	9,286%	3,17796	0,00180
SMB	16,507%	8,230%	2,00575	0,04667
HML	5,945%	14,478%	0,41063	0,68193
MOM	-1,371%	11,334%	-0,12094	0,90390

Figure 14 EBIT % Strategy - Regression Output

Question III: *How does the weighting affect the risk profile of the portfolios?*

Best Performing Stocks Measured on RoIC 2018		Best Performing Stocks Measured on EY 2018	
Name	**Beta**	**Name**	**Beta**
NetEnt AB Class B	0,61	SAS AB	-0,15
eWork Group AB	1,05	NAXS AB	0,27
Swedish Match AB	0,62	Lucara Diamond Corp.	1,09
Dedicare AB	1,13	Rottneros AB	2,24
Axfood AB	0,44	Duroc AB Class B	1,18
BioGaia AB Class B	0,88	Arctic Paper S.A.	1,01
Micro Systemation AB Class B	2,55	Tethys Oil AB	0,80
Niloerngruppen AB Class B	0,96	Mycronic AB	2,59
Mycronic AB	2,59	JM AB	0,85
Evolution Gaming Group AB	-0,33	KABE Group AB Class B	0,28
Kindred Group	-0,16	Karolinska Development AB	0,66
Lucara Diamond Corp.	1,09	Besqab AB	1,61
CellaVision AB	1,79	Kappahl AB	0,85
JM AB	0,85	Ferronordic Machines AB	N/A
Mertiva AB Class A	0,12	Bong AB	0,57
G5 Entertainment AB	0,96	Granges AB	0,93
Karolinska Development AB	0,66	Cantargia AB	1,65
Concentric AB	1,07	Lundin Mining Corporation - Sweden	2,12
GARO AB	0,29	Lundin Mining Corporation - Canada	1,77
Sectra AB Class B	1,40	RNB RETAIL AND BRANDS AB	0,62
Average	***0,93***	***Average***	***1,10***

Figure 15 Beta Tables, Sources: Avanza Bank and Yahoo! Finance

The tables in Figure 15 presents the betas from the 20 best performing stocks measured on RoIC and EY, respectively. This is based on 2018 data. It is clear that there is some degree of connectedness between EY and higher beta values. This might not be surprising, considering our returns. However, it strengthens our hypothesis that this is a good framework for managing risk. One can observe that as we increase the EY emphasis, the returns increase. Additionally, when setting equal emphasis on RoIC and EY, we should approach a beta of one. The main conclusion here is that the betas are not extreme in any of the cases and that the portfolios are close to the market beta. Regardless, the portfolios managed to generate outstanding returns and in excess of the risk assumed.

4.1. Summary of Results

In this final section of the result, we briefly summarize the results in relation to our hypothesis formulation in Section 3.1. We cannot support hypothesis 1 as we have successfully been able to prove that it is possible to systematically increase the abnormal returns within our weighting framework. As we increase the weighting towards EY dominance, we see an upward trend in the alphas. This proves that it is possible to deviate from the original MFI structure and by so doing, increase alpha. Secondly, we find strong evidence that RoIC and EY are powerful predictors of future returns when compared to similar metrics. This finding is a strong explanation for why we managed to generate excess returns for all possible weighting combinations. Finally, we have partial evidence which disproves our third hypothesis. In fact, we find that the betas and the risk profile of the portfolios should increase (decrease) as a result of excessive weighting toward EY (RoIC).

H1:	It is not possible to increase the returns without increasing risk using a systematic approach to the weighting framework.	Not supported
H2:	RoIC and EY does not differ from similar metrics in their ability to predict future returns.	(Partially) Not Supported
H3:	The risk profile of the portfolios remains unchanged as the weighting combinations are altered.	(Partially) Not Supported

Table 1: Summary of Results

5. Discussion and Conclusion

5.1. Discussion

When an investor can back claims that they can beat the market, they will generally attract a lot of attention. There is no exception to Greenblatt's Magic Formula. We have discussed various reports that back-test the strategy, and most of them seems to confirm what Greenblatt presented in his book back in 2006. This is quite interesting as the power of the formula does not seem to have decreased over the, although relatively short, time span since its first introduction. Thus, it seems as though Greenblatt has provided a simple system focusing on fundamental analysis that can far outperform relevant indices. In this paper, we have taken an actively different stance from previous research and tests, through constructing a proprietary framework for managing risk and returns.

Our goal with this study was to examine if we could achieve systematically higher risk-adjusted returns by using a specific weighting to our metrics. We found that this was in fact possible, which can be observed in Figure 11 and Figure 12 in the result chapter. In both figures we can clearly see how the return varies between the differently weighted portfolios. A relevant finding relating to the Fama-French test is the disconnection between the weighting combination that generates the highest alpha and the highest returns. Nevertheless, when we perform the Carhart's test we can observe how the portfolio with the highest return also generates the highest alpha. In both tests, the alpha trends upward as a result of increasing the weighting toward EY and downward when increasing the weighting toward RoIC. Relating back to our hypothesis formulation, our findings cannot support the first hypothesis. It is quite clear that we can in fact increase the abnormal returns by using a systematic approach, in our dataset by pushing on the EY emphasis.

In Figure 7 in our result chapter, we show that the two worst performing portfolios within our framework (RoIC=0, EY=1 and RoIC=0.2 and EY=1) produces far higher returns than the OMXSGI. In fact, the "worst" portfolio outperforms the index by a factor of almost three. The reason we can observe these large discrepancies between the MFI portfolios and the index relates to the compounding effect that is created through resistance to downturns and overall stellar performance during upturns. In Appendix 1, it is possible to observe that during bull-market years, the deviation between the MFI portfolio and the index are so substantial that they produce a protection for the underperforming years. Specifically, our portfolios gain the most in the years 2004-2005, 2009, 2011, and 2015-2016. What is also interesting is that the portfolios that emphasize on EY have larger dips during downturns but manages to recoup these losses by generating sufficiently high returns in the upturns. On the other hand, the losses to the portfolios that emphasize on RoIC more closely matches those of the index. However, these portfolios do not recoup as much during the upturns. Thus, the TR for the RoIC emphasized portfolios are lower than the EY emphasized portfolios.

How can we explain the abnormal returns in relation to the two metrics? In Chapter 2 of this paper, we touched upon how the metrics are constructed and what they represent.

RoIC is seen as a quality ratio, which means that a high RoIC will signal that the underlying firm is efficient in employing its invested capital in order to generate profits, ceteris paribus. On the other hand, a high EY signals that the firm can recoup much of its enterprise value in one year's operating profit. This will imply a relatively undervalued firm, ceteris paribus. At first, we hypothesized that the combination of these two metrics would result in optimal portfolios. The rationale behind our reasoning is intuitive but is closely connected to the argument that finding high-quality firms at a low valuation should lead to outstanding returns over time. We argue that most of the alphas are causal outcomes of this reasoning.

An important caveat to this paper relates to the positive alphas that occur when focusing completely on RoIC or EY. In these cases, we stray away from our hypothesis that the combination of the two metrics should perform better than focusing on them individually. According to Fama and French (1993), value portfolios should not be able to generate positive and significant alphas. The HML component should, at least in theory, be able to remove any excess returns stemming from such portfolios. However, when we weight the two metrics in favor of EY, we are in essence creating value portfolios. The resulting alpha can therefore be regarded as quite contradictory. To clarify these results, we will lay out some explanations.

The first explanation relates to the article Betting against beta by Frazzini and Pedersen (2014), which we have discussed in section 2.2.3. In their study, they reveal that low-beta portfolios generate positive alphas on average. However, Sweden is the only country in that report in which a long high-beta strategy is profitable and generates a substantial alpha. We have also previously uncovered that value stocks tend to carry greater risk and higher beta. Therefore, we argue that the alphas of the EY-portfolios could be a natural response to the larger beta values (when compared to the quality-portfolio equivalents). Secondly, it is possible that the Fama-French factors have become inadequate in their roles as explanatory variables for excess returns. Bear in mind that the framework for these factors were constructed more than 25 years ago.

Another possibility, which might be more likely, is the fact that there is a significant difference between EY as a metric and PtB/BtM, which is used to construct the HML factor. In our result, we created a regression output between the returns from pure low-PtB portfolios and the C4FM (see Figure 13). One can observe that this strategy did not generate positive alpha during the period 2004-2016. Through analyzing this outcome, we find evidence which supports the idea that there is a significant difference between HML and EY as predicative measures. Likewise, we performed the same type of test for portfolios created on high operating profitability. As there is no factor in any of the intercept tests which deals with the profitability of the underlying firms, it is hardly no surprise that this strategy was able to generate alpha. The size of the alpha was also similar to that of the portfolios which focus exclusively on RoIC. As predictive measures, EY seems to be quite different from PtB and since profitability is not included as a factor in the regressions, we have likely provided an answer to this important caveat. Finally, it is possible that there are some market dynamics that can further explain this phenomenon. In the subsequent paragraphs of this section, we will explain how the different returns behave over the investing horizon.

We observe our returns through the lens of an in-sample test. Thus, we divided the sample period into two smaller test periods. The first period is set between 2004 and 2010, and the second period is from 2011 to 2018. In the first period, the portfolios with more emphases towards EY outperforms the portfolios with RoIC emphases. This is shown in Appendix 4. Figures 4, 5, and 6 in the result section display that in 2008, the TR between all the portfolios and the index were relatively equivalent. The differences in TR between the weighted portfolios can first be observed in the years after our strategy begins to outperform the index (i.e. post 2008/2009).

In the second time period of the in-sample test, we observe a shift in TR. Between the years 2011 and 2018, the portfolio that is exclusively based on RoIC outperforms the EY portfolio. The average returns for the two time-periods amount to 22.3% versus 18.8%, respectively. However, the EY portfolio manage to fully offset this shift due to its unmatched outperformance in the first time-period. Nevertheless, this change in return dominance between EY and RoIC is interesting. It is well known that the regulations, laws and investing strategies which existed before the 2008 financial crises were very different compared to the ones after. Investors accept considerably less risk today than they did before the crisis, and in the last couple of years their strategies have also started to shift towards more sustainable companies. These are plausible explanations to this shift, but further research needs to be done in order to answer this question fully.

In regard to an important topic in financial academia, we will try to explain whether the abnormal returns found for each weight relates to mispricing or a risk premium. By studying the return distribution between the different weighting combinations, we see that our portfolios generally outperform the index’s annual percentage return in bull markets and underperform the index in bear markets (see Appendix 1). This is a classical characteristic of portfolios with higher than average betas. We then argue that the large returns should relate to some form of risk premium. However, it is not a pure risk premium as we still generate alpha. There should therefore be some inherent mispricing or market dynamic that could further explains our results. In addition, we believe that the MFI framework is a rational approach to stock-picking that could be overlooked by many of the larger investors. As is known, strategies that are popularized by investors tend to lose their edge as they become increasingly widespread. Also, the framework does not allow for exogenous phycological factors to impact the returns in any way, as stocks are only bought and sold at one point in time per year.

Although the main academic contribution of this paper is the presentation of abnormal returns relating to the FF3F and the C4FM, we wish to briefly steer the reader’s focus in another direction. While it might seem trivial, we find it interesting that the model of weighting RoIC and EY creates a systematic framework for managing risk and returns. When focusing on quality, the investor hedges against downside risk but limits the upside potential. On the other hand, when focusing on value, the investor increases risk exposure but gain a higher upside. This is evident from reading the beta tables in Figure 15 as well as studying the total returns in Appendix 4. Nonetheless, the baseline is that all these strategies produces outstanding returns in excess of the risk assumed. Therefore, our weighting strategy allows the investors to create portfolios which matches their risk profile.

5.2. Future Research

As stated above, one area for future research is to analyze the shift from EY to RoIC in TR when performing the in-sample test. Obviously, the investing landscape changed after the 2008 crisis, but it would be interesting to see which elements contributed the most. Another interesting area for future research is to examine the return in relation to other factors than the ones used in FF3F and C4FM. It is possible that factors such as RMW (which focuses on profitability) would better explain the results and remove any excess returns. Finally, studying the strategy in more stock markets to see whether our conclusions hold internationally would be a good contribution.

5.3. Conclusion

In this paper, we have examined Joel Greenblatt's Magic Formula strategy in a new light. We strived to decrypt the underlying metrics, RoIC and EY, of this strategy and test their respective contribution to the total returns over assigned time span, 2004-2018. In addition to testing the strategy on the Swedish market, with new data and for more recent time samples, we also test if the weighting of the different metrics affects the total returns. We find that it does so quite significantly. We are successful in concluding that the returns can be enhanced by weighting the metrics more heavily in favor of EY. We partially attribute this to the extra risk assumed when following a value-based investment strategy. In turn, we then view EY as a proxy for risk as a high EY could be a consequence of firm-specific financial distress. It is noteworthy that although the risk is increased as a result for weighting in favor of EY, the returns produced by doing so are sufficiently high to offset the risk and therefore generate positive alpha. This creates a systematic approach to the framework that allows investors to experiment with different weights to match their risk profile. Moreover, we find positive and statistically significant alphas for each weight tested. Although this might seem contradictory in relation to Fama and French's 1993 paper, we have laid out the mechanisms that explains how this is possible. Most probably these findings relate to the inherent difference in predictiveness between the metrics used for producing the portfolios, and the metrics used to construct the testable factors.

Another prominent observation can be found in our in-sample test where we plot aggregated total returns for the different weights. We see that in the first time-period, which consists of the years between 2004 and 2010, the EY portfolios vastly outperforms the RoIC portfolios. However, in the second time period, the opposite is true. We have an idea that this relates to the difference in investment climate before and after the financial crisis in 2008/2009. It is plausible that investors became more risk averse after the recession, which shifted investor sentiment towards quality rather than value.

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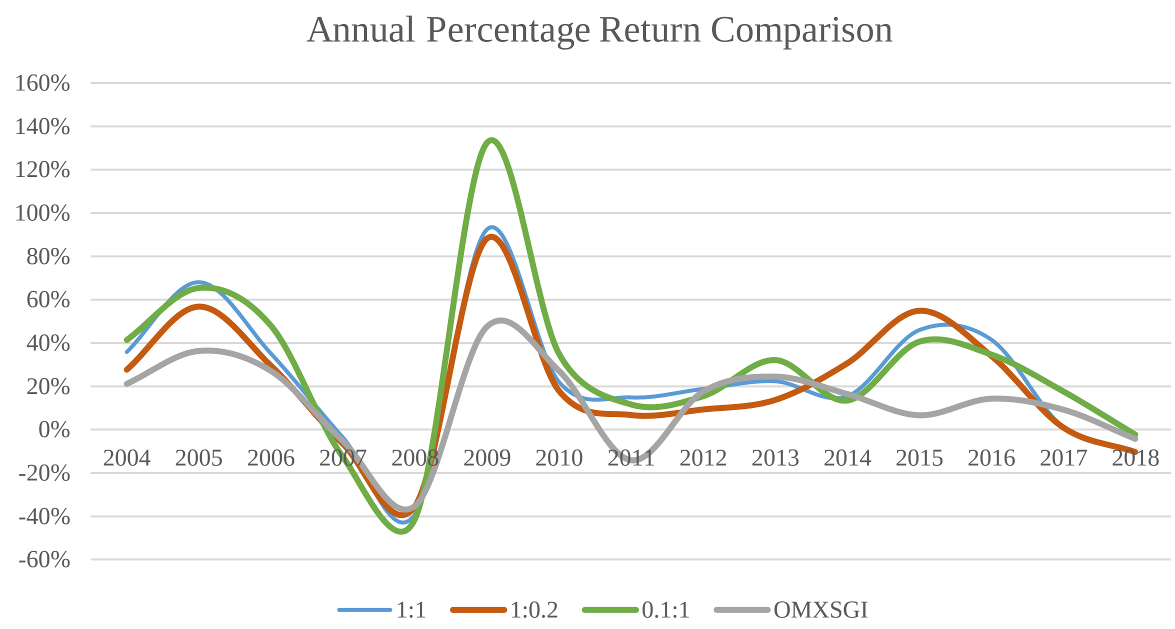
7. Appendices

Appendix 1: Details of Annual Percentage Return



Appendix 2: Defintion of Beta

$$\beta = \frac{Cov(r_i, r_m)}{Var(r_i)}$$

Source: Berk & DeMarzo (2017)

Appendix 3: Average Monthly Returns

RoIC:EY	Mean Return (mo)	RoIC:EY	Mean Return (mo)
1:1	1,580%	1:1	1,580%
1:0.9	1,551%	0.9:1	1,577%
1:0.8	1,578%	0.8:1	1,593%
1:0.7	1,588%	0.7:1	1,602%
1:0.6	1,607%	0.6:1	1,613%
1:0.5	1,583%	0.5:1	1,631%
1:0.4	1,583%	0.4:1	1,670%
1:0.3	1,468%	0.3:1	1,732%
1:0.2	1,385%	0.2:1	1,737%
1:0.1	1,443%	0.1:1	1,848%
1:0	1,452%	0:1	1,774%

Appendix 4: All Portfolio's Total Return

ROIC	**EY**																
1	**1**	(End of year)															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	135 770	228 075	308 114	296 698	180 395	347 041	423 248	485 864	576 688	705 125	812 981	1 185 793	1 678 115	1 694 747	1 520 122
Return MFI		35,77%	67,99%	35,09%	-3,71%	-39,20%	92,38%	21,96%	14,79%	18,69%	22,27%	15,30%	45,86%	41,52%	0,99%	-10,30%
Return OMX30		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	30,04%							Avg. return/year 2011-2018, MFI	18,64%
							Avg. return/year 2004-2010, OMX	0,17%							Avg. return/year 2011-2018, OMX	0,09%
ROIC	**EY**																
1	**0,9**																
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	135 770	228 075	308 114	281 989	171 452	318 767	386 841	445 352	528 604	652 722	792 738	1 131 280	1 610 331	1 626 291	1 458 720
Return MFI		35,77%	67,99%	35,09%	-8,48%	-39,20%	85,92%	21,36%	15,13%	18,69%	23,48%	21,45%	42,71%	42,35%	0,99%	-10,30%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	28,35%							Avg. return/year 2011-2018, MFI	19,31%
							Avg. return/year 2004-2010, OMX	0,17							Avg. return/year 2011-2018, OMX	0,09
ROIC	**EY**																
1	**0,8**																
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	135 770	228 075	312 656	290 671	178 299	331 009	397 747	457 907	543 506	672 859	817 195	1 166 182	1 660 012	1 694 604	1 526 359
Return MFI		35,77%	67,99%	37,09%	-7,03%	-38,66%	85,65%	20,16%	15,13%	18,69%	23,80%	21,45%	42,71%	42,35%	2,08%	-9,93%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	28,71%							Avg. return/year 2011-2018, MFI	19,53%
							Avg. return/year 2004-2010, OMX	0,17							Avg. return/year 2011-2018, OMX	0,09
ROIC	**EY**																
1	**0,7**																
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	133 028	227 331	319 763	297 277	193 192	358 657	419 312	456 385	523 460	648 043	836 588	1 193 857	1 699 406	1 734 819	1 556 177
Return MFI		33,03%	70,89%	40,66%	-7,03%	-35,01%	85,65%	16,91%	8,84%	14,70%	23,80%	29,09%	42,71%	42,35%	2,08%	-10,30%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	29,30%							Avg. return/year 2011-2018, MFI	19,16%
							Avg. return/year 2004-2010, OMX	0,17							Avg. return/year 2011-2018, OMX	0,09
ROIC	**EY**																
1	**0,6**																
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	130 821	227 116	319 460	306 588	199 243	369 891	435 367	475 757	548 508	679 052	871 028	1 243 004	1 769 365	1 806 236	1 614 383
Return MFI		30,82%	73,61%	40,66%	-4,03%	-35,01%	85,65%	17,70%	9,28%	15,29%	23,80%	28,27%	42,71%	42,35%	2,08%	-10,62%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	29,91%							Avg. return/year 2011-2018, MFI	19,14%
							Avg. return/year 2004-2010, OMX	0,17							Avg. return/year 2011-2018, OMX	0,09
ROIC	**EY**																
1	**0,5**																
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	124 836	213 330	290 413	272 741	192 589	361 850	433 268	476 274	556 512	664 895	840 966	1 291 017	1 769 779	1 813 495	1 596 176
Return MFI		24,84%	70,89%	36,13%	-6,09%	-29,39%	87,89%	19,74%	9,93%	16,85%	19,48%	26,48%	53,52%	37,08%	2,47%	-11,98%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	29,14%							Avg. return/year 2011-2018, MFI	19,23%
							Avg. return/year 2004-2010, OMX	0,17							Avg. return/year 2011-2018, OMX	0,09

ROIC	**EY**															
1	**0,4**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	130 437	211 929	284 223	271 835	186 018	358 942	424 343	466 463	522 749	624 557	789 945	1 242 649	1 674 470	1 709 660	1 544 184
Return MFI		30,44%	62,48%	34,11%	-4,36%	-31,57%	92,96%	18,22%	9,93%	12,07%	19,48%	26,48%	57,31%	34,75%	2,10%	-9,68%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	28,90%							Avg. return/year 2011-2018, MFI	19,05%
							Avg. return/year 2004-2010, OMX	16,89%							Avg. return/year 2011-2018 OMX	8,71%
ROIC	**EY**															
1	**0,3**	(End of year)														
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	126 782	205 779	266 444	255 193	174 239	333 596	402 280	423 763	463 138	521 958	665 200	1 052 564	1 466 531	1 521 051	1 347 629
Return MFI		26,78%	62,31%	29,48%	-4,22%	-31,72%	91,46%	20,59%	5,34%	9,29%	12,70%	27,44%	58,23%	39,33%	3,72%	-11,40%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	27,81%							Avg. return/year 2011-2018, MFI	18,08%
							Avg. return/year 2004-2010, OMX	16,89%							Avg. return/year 2011-2018, OMX	8,71%
ROIC	**EY**															
1	**0,2**	(End of year)														
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	127 592	199 962	258 912	241 829	156 130	293 732	346 131	369 205	403 282	458 202	598 039	925 862	1 240 891	1 252 503	1 122 148
Return MFI		27,59%	56,72%	29,48%	-6,60%	-35,44%	88,13%	17,84%	6,67%	9,23%	13,62%	30,52%	54,82%	34,03%	0,94%	-10,41%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	25,39%							Avg. return/year 2011-2018, MFI	17,43%
							Avg. return/year 2004-2010, OMX	16,89%							Avg. return/year 2011-2018, OMX	8,71%
ROIC	**EY**															
1	**0,1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	122 735	193 950	243 570	223 508	149 228	276 560	332 297	364 417	394 105	454 309	605 813	945 033	1 200 648	1 410 519	1 248 789
Return MFI		22,73%	58,02%	25,58%	-8,24%	-33,23%	85,33%	20,15%	9,67%	8,15%	15,28%	33,35%	55,99%	27,05%	17,48%	-11,47%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	24,34%							Avg. return/year 2011-2018, MFI	19,44%
							Avg. return/year 2004-2010, OMX	16,89%							Avg. return/year 2011-2018, OMX	8,71%
ROIC	**EY**															
1	**0**	(End of year)														
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	116 570	182 633	206 294	189 123	128 008	232 574	275 350	297 962	322 235	384 389	513 864	858 420	1 098 848	1 352 298	1 230 841
Return MFI		16,57%	56,67%	12,96%	-8,32%	-32,32%	81,69%	18,39%	8,21%	8,15%	19,29%	33,68%	67,05%	28,01%	23,07%	-8,98%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	20,81%							Avg. return/year 2011-2018, MFI	22,3%
							Avg. return/year 2004-2010, OMX	16,89%							Avg. return/year 2011-2018, OMX	8,71%
ROIC	**EY**															
0,9	**1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	135 770	228 238	318 986	307 167	188 191	362 038	451 068	517 939	593 936	726 215	819 984	1 196 007	1 692 569	1 722 193	1 518 042
Return MFI		35,77%	68,11%	39,76%	-3,71%	-38,73%	92,38%	24,59%	14,83%	14,67%	22,27%	12,91%	45,86%	41,52%	1,75%	-11,85%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	31,17%							Avg. return/year 2011-2018, MFI	17,74%
							Avg. return/year 2004-2010, OMX	16,89%							Avg. return/year 2011-2018, OMX	8,71%

ROIC	**EY**															
0,8	**1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	138 145	232 231	321 941	294 064	179 505	355 850	443 358	519 178	595 357	727 951	821 945	1 198 867	1 724 154	1 764 672	1 555 484
Return MFI		38,14%	68,11%	38,63%	-8,66%	-38,96%	98,24%	24,59%	17,10%	14,67%	22,27%	12,91%	45,86%	43,82%	2,35%	-11,85%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
						Avg. return/year 2004-2010, MFI		31,44%						Avg. return/year 2011-2018, MFI		18,39%
						Avg. return/year 2004-2010, OMX		16,89%						Avg. return/year 2011-2018, OMX		8,71%
ROIC	**EY**															
0,7	**1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	144 132	242 296	338 019	308 750	188 470	373 622	463 387	556 122	631 770	772 475	872 217	1 213 920	1 745 802	1 786 828	1 575 015
Return MFI		44,13%	68,11%	39,51%	-8,66%	-38,96%	98,24%	24,03%	20,01%	13,60%	22,27%	12,91%	39,18%	43,82%	2,35%	-11,85%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
						Avg. return/year 2004-2010, MFI		32,34%						Avg. return/year 2011-2018, MFI		17,79%
						Avg. return/year 2004-2010, OMX		16,89%						Avg. return/year 2011-2018, OMX		8,71%
ROIC	**EY**															
0,6	**1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	144 132	245 590	346 342	313 611	184 644	370 737	459 809	552 879	628 086	767 913	867 066	1 204 464	1 754 784	1 796 021	1 583 117
Return MFI		44,13%	70,39%	41,02%	-9,45%	-41,12%	100,79%	24,03%	20,24%	13,60%	22,26%	12,91%	38,91%	45,69%	2,35%	-11,85%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
						Avg. return/year 2004-2010, MFI		32,83%						Avg. return/year 2011-2018, MFI		18,01%
						Avg. return/year 2004-2010, OMX		16,89%						Avg. return/year 2011-2018, OMX		8,71%
ROIC	**EY**															
0,5	**1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	144 132	245 590	347 609	318 998	193 498	382 586	474 505	569 188	646 448	806 096	910 179	1 264 353	1 809 689	1 872 401	1 650 443
Return MFI		44,13%	70,39%	41,54%	-8,23%	-39,34%	97,72%	24,03%	19,95%	13,57%	24,70%	12,91%	38,91%	43,13%	3,47%	-11,85%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
						Avg. return/year 2004-2010, MFI		32,89%						Avg. return/year 2011-2018, MFI		18,10%
						Avg. return/year 2004-2010, OMX		16,89%						Avg. return/year 2011-2018, OMX		8,71%
ROIC	**EY**															
0,4	**1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	142 034	242 014	363 321	330 367	200 394	407 197	513 593	616 076	681 509	859 707	962 535	1 356 998	1 929 166	1 986 183	1 750 738
Return MFI		42,03%	70,39%	50,12%	-9,07%	-39,34%	103,20%	26,13%	19,95%	10,62%	26,15%	11,96%	40,98%	42,16%	2,96%	-11,85%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
						Avg. return/year 2004-2010, MFI		34,78%						Avg. return/year 2011-2018, MFI		17,87%
						Avg. return/year 2004-2010, OMX		16,89%						Avg. return/year 2011-2018, OMX		8,71%
ROIC	**EY**															
0,3	**1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	140 408	232 823	342 836	319 430	185 284	394 125	507 855	592 622	651 048	839 785	951 968	1 357 972	1 941 374	2 155 720	1 932 656
Return MFI		40,41%	65,82%	47,25%	-6,83%	-42,00%	112,71%	28,86%	16,69%	9,86%	28,99%	13,36%	42,65%	42,96%	11,04%	-10,35%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
						Avg. return/year 2004-2010, MFI		35,18%						Avg. return/year 2011-2018, MFI		19,40%
						Avg. return/year 2004-2010, OMX		16,89%						Avg. return/year 2011-2018, OMX		8,71%

ROIC	**EY**															
0,2	**1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	140 408	231 118	334 751	306 764	177 937	404 592	511 435	590 428	669 127	863 105	936 770	1 332 059	1 804 951	2 074 841	1 916 952
Return MFI		40,41%	64,60%	44,84%	-8,36%	-42,00%	127,38%	26,41%	15,45%	13,33%	28,99%	8,53%	42,20%	35,50%	14,95%	-7,61%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	36,18%							Avg. return/year 2011-2018, MFI	18,92%
							Avg. return/year 2004-2010, OMX	16,89%							Avg. return/year 2011-2018, OMX	8,71%
ROIC	**EY**															
0,1	**1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	141 330	233 679	345 766	301 917	177 056	411 430	555 407	619 604	714 621	943 708	1 069 741	1 503 086	2 023 570	2 379 830	2 323 060
Return MFI		41,33%	65,34%	47,97%	-12,68%	-41,36%	132,37%	34,99%	11,56%	15,34%	32,06%	13,36%	40,51%	34,63%	17,61%	-2,39%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	38,28%							Avg. return/year 2011-2018, MFI	20,33%
							Avg. return/year 2004-2010, OMX	16,89%							Avg. return/year 2011-2018, OMX	8,71%
ROIC	**EY**															
0	**1**															
YEAR	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Performance	100 000	145 575	243 624	350 150	308 140	189 640	434 869	547 063	568 859	663 136	928 253	1 125 378	1 465 792	1 918 910	2 112 646	2 053 913
Return MFI		45,58%	67,35%	43,73%	-12,00%	-38,46%	129,31%	25,80%	3,98%	16,57%	39,98%	21,24%	30,25%	30,91%	10,10%	-2,78%
Return OMX		21,07%	36,26%	27,05%	-5,39%	-35,32%	47,46%	27,07%	-14,21%	17,49%	24,41%	16,40%	6,56%	14,21%	9,17%	-4,33%
							Avg. return/year 2004-2010, MFI	37,33%							Avg. return/year 2011-2018, MFI	18,78%
							Avg. return/year 2004-2010, OMX	16,89%							Avg. return/year 2011-2018, OMX	8,71%