In-depth analysis of Greenblatt's magic formula: risk or true value?

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Abstract

This paper's focus is on the risk-adjusted performance over time of the value investing framework "the magic formula" by Greenblatt (2006). It is shown that investing in stocks within the Russell 3000 index according to the magic formula would have yielded 12.23 percent of gross annual return from June 1996 to May 2017, compared to an annual average of almost 7.75 percent on the Russell 3000 value-weighted index over the same period. However, it appears that these high returns can be largely attributed to risk. Furthermore, there is no notable change in risk-adjusted performance before and after the publication of Greenblatt's book. Nonetheless, the metrics used in the stock selection process do produce significant positive 3-factor alphas on descriptive (ex-post) basis, implying that they are valuable proxies for quality and value among the cross-section of stocks if one can identify these traits before they are priced into the market.

Keywords: Magic formula, Value, Glamour, Risk, 3-Factor Model

Content

1. Introduction

The stock market has always attracted fortune seekers. Many people have tried making large profits from trading public securities, and many have failed. However, some investors seem to be able to persistently perform well. They earn a lot of money by carefully picking certain stocks according to a strategy, and hold on to their strategies long enough to reap the fruits.

A prevalent example of such a strategy is value investing. Introduced by Graham and Dodd in 1934, it suggests buying quality stocks at a cheap price. Many adaptions and variations have been published since, with one of the latest being *The Little Book that Beats the Market* by Joel Greenblatt (2006). Greenblatt claims that his strategy has consistently outperformed the market.

The question arises if the returns generated by this strategy can be truly attributed to the skill of the investor, or that they are merely a product of luck or the effect of larger risk exposure. Evidence by Novy-Marx (2013, 2014) suggests that Greenblatt's strategy is indeed capable of producing abnormal returns, even when correcting for risk using a 3-factor model as defined by Fama and French (1993). However, the efficient market hypothesis dictates that new information will be fully priced into the market after it is published (Fama, 1970). As such, it is to be expected that the positive 3-factor risk-adjusted returns of Greenblatt's formula will quickly diminish if not disappear at all after the first publication of the book, if there was no risk-based explanation in the first place.

This paper starts with a theoretical foundation in which underlying economic theories are explained and earlier evidence is presented. Thereafter, the data and methodology are discussed. Then the results are presented and compared with economic theory. Here, empirical evidence is shown that the magic formula is not capable of generating significant 3-factor alphas, but that Earnings Yield and ROIC are nonetheless valuable as proxies for value and quality. Moreover, the performance of the magic formula before and after the publication year 2006 is tested, but found to be largely the same. Lastly, a conclusion is drawn from the empirical results, with eye for future research possibilities.

2. Theoretical Foundations

In this section, the theoretical foundations used in the analysis of the magic formula are presented. First of all, the hypothesis of the efficient market, and uncertainty and risk in financial decision making are introduced. Subsequently, the origin and evolution of value strategies are disclosed. Then the relation of value strategies to risk is discussed. The section closes with a review of Greenblatt's strategy.

2.1 Efficient markets

Introduced by Fama in 1970, the Efficient Market Hypothesis (EMH) states that the capital market is efficient if the prices on the market fully reflect all available information. Three different forms of the EMH are distinguished: (i) the weak form, in which the market reflects all historical price data; (ii) the semi-strong form, in which the market reflects all historical price data and all publicly available information[1]; and (iii) the strong form, which extends the semi-strong form to all private information being priced into the market as well. Fama (1970) finds empirical evidence for the first two forms of the EMH, but no unequivocal evidence is found for the third. As such, it is to be expected that one cannot profit from the use of technical[2] or fundamental[3] analysis. Consequently, all stock market returns should be explicable by expected returns and risk, or uncertainty, with the exception of profits made from inside trading[4]. However, the semi-strong form is not ubiquitous either, as Basu (1977) shows some empirical evidence against it.

2.2 Different measures of risk

Nonetheless, it follows that capital markets are, at least to some extent, considered efficient. From there, it is inferred that returns on capital markets should be justified by risk. To be able to analyze the relation between risk and rewards, one needs first to establish a sound definition of risk. Through the years, several definitions have been used, three of which will be documented in this subsection. The first is the Sharpe (1964) – Lintner (1965) Capital Asset Pricing Model (CAPM), which measures risk as the covariance with the market, plus risk that can be directly attributed to the firm itself. The second is the Sharpe ratio, which measures the ratio of the returns in excess of the risk-free rate to their standard deviation. The third is the Fama and French (1993) 3-factor

[1] For example, earnings announcements, seasoned stock offerings, et cetera.
[2] Technical analysis refers to using historical stock price data to find patterns that predict future stock movement.
[3] Fundamental analysis refers to picking stocks on the basis of fundamental accounting data and ratios, such as earnings to price and book value to market value.
[4] The term "inside trading" is used to describe the process of trading on the basis of private information, which could still offer arbitrage possibilities under the semi-strong form of the EMH.

model, which introduces the size of the company and the book to market ratio as additional measures of risk.

2.2.1 Systematic and unsystematic risk

When people rationally invest money, they will try to maximize expected return. That means that if one stock is going to earn more than all other stocks, they would prefer to only invest in that certain stock. However, the stock market is highly volatile and the future unpredictable. Therefore, the expected return of a stock is subject to a lot of uncertainty, or risk[5]. This is where the law of large numbers comes into play. If the investor were to buy a selection of stocks that all have high expected returns, then the variance of the returns on this portfolio would go down dramatically. Hence, the part of the variance associated with each of the specific stocks is now marginalized and spread out over the entire portfolio[6], whereas the portfolio returns themselves would be close to the average of expected returns of the stocks in the portfolio (Markowitz, 1952).

Forming diversified portfolios in a similar fashion could indeed largely eliminate the risk associated with individual stocks. The only remaining risk factor would be the exposure to market volatility. This is called systematic risk in the Sharpe (1964) – Lintner (1965) Capital Asset Pricing Model (CAPM). Systematic risk is the part of a stock's return that is correlated with the market return. The remainder (the variance of $\epsilon_{i,t}$ in regression (1)) is called unsystematic, firm-specific or idiosyncratic risk. The exposure of a stock's return to the market return can be estimated through formula (1) using an ordinary least-squares (OLS) regression and is often denoted as β_i or Beta for stock *i.*

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i * \left(R_{m,t} - R_{f,t}\right) + \epsilon_{i,t} \tag{1}$$

α_i is the part of the return on stock i that is not explained by covariation with the market;
$R_{i,t}$ denotes the return of firm i at time t;
$R_{m,t}$ denotes the return of the benchmark market index at time t;
$R_{f,t}$ is the risk-free rate at time t;
$\epsilon_{i,t}$ is the error term for the given stock at the given time.

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[5] Strictly speaking, uncertainty means neither the chances nor the outcomes are known, whereas risk is defined as not knowing the outcome, but having information on the distribution of chances (Mauboussin, 2007). Most market models use risk to explain returns, although in reality it most often is uncertainty that plagues the investor.

[6] When looking at equation (1), it becomes clear that if $R_{i,t}$ resembles the return of stock i at time t, and a portfolio is formed over N stocks, then the equal-weighted portfolio return at time t would yield $\frac{\sum_{i=1}^{N} R_{i,t}}{N}$ and the average error tem $\frac{\sum_{i=1}^{N} \epsilon_{i,t}}{N}$ would approach 0 when N becomes larger, as the error terms are by definition normally distributed with a mean of zero. As the error terms are closer to zero, so is their variance over time. Thus, increasing portfolio size N decreases the variance of the error terms, caso quo risk.

Jensen's alpha and the Sharpe ratio

In a similar fashion as for individual securities, the market exposure of an entire portfolio or fund can be calculated. This can be done by letting $R_{i,t}$ from formula (1) be the portfolio return for portfolio i at time t. Now α_i will actually cover the part of the portfolio's return that is not explained by the variance of the market, if β_i can be assumed to on average remain at a certain level for a given portfolio i (Jensen, 1968). In effect, a positive (negative) alpha indicates that the portfolio earns more (less) than what would be justified by its exposure to market movement. It would be expected to be around zero for a market-mimicking portfolio, and it is therefore extraordinary if the alpha is positive. For this reason, the CAPM intercept is often referred to as abnormal return. In this paper, the terms Jensen's alpha and abnormal return will be used as synonyms.

Another widespread measure for evaluating return against risk is the Sharpe ratio. The Sharpe ratio measures the portfolio's return in excess of the risk-free rate per unit of volatility, or risk. The portfolio return in excess of the risk-free rate, given by $(R_{i,t} - R_{f,t})$ and referred to as excess return in the rest of this paper, is simply the return on portfolio i minus the risk-free rate for the given period t. The ratio itself is calculated by dividing the excess portfolio return by the standard deviation of the excess portfolio return (Sharpe, 1966, 1994). A more elaborate explanation of the Sharpe ratio and it's calculation, including printed equations, can be found in section 3.2.2.

2.2.2 The 3-factor model

Although the CAPM was a breakthrough in financial research, it still leaves common variation in the cross-section of stock returns that is not explained by the market factor (Fama & French, 1992). To capture this remaining variance in stock returns, Fama and French (1993) introduced two new risk factors in addition to the market factor. The first one, Small Minus Big (SMB), is based on Market Equity (ME). Market Equity is calculated by multiplying a firm's outstanding shares with the share price. The second factor is named High Minus Low (HML), and is based on the firm's book-to-market ratio, calculated as Book Equity (BE) to ME.

The model is unique in the way the factors are calculated. First, all stocks of the benchmark are divided into two groups on the median of Size. Simultaneously, three groups are formed by dividing the stocks on the 30th and 70th percentiles of book-to-market. Thereafter, six portfolios are formed, one for each combination of groups. The value weighted average returns for each of these six portfolios[7] form the basis for the risk factors. To calculate SMB, the simple average of all three portfolios' returns with Big stocks are subtracted from the simple average of all three portfolios' returns with Small stocks. HML is calculated by subtracting the simple average of both

[7] It follows from the portfolio formation procedure that the portfolios are not necessarily of the same size.

Low book-to-market portfolios' returns from the simple average of returns generated by the two High book-to-market portfolios (Fama & French, 1993). This method ensures the absence of cross-effects from size on HML and from book to market on SMB.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i * \left(R_{m,t} - R_{f,t}\right) + s_i * SMB_t + h_i * HML_t + \epsilon_{i,t} \quad (2)$$

α_i is the part of the return on stock i that is not explained by covariation with the market, HML or SMB;
β_i is the factor loading to the market risk factor $(R_{m,t} - R_{f,t})$;
s_i denotes the factor loading s of stock i to factor SMB;
h_i denotes the factor loading h of stock i to the factor HML;
$(R_{i,t} - R_{f,t})$ denotes the excess return of firm i at time t (return in excess of the risk-free rate);
$(R_{m,t} - R_{f,t})$ denotes the return of the benchmark market index at time t in excess of the risk-free rate;
SMB_t is the return on the Small minus Big portfolio at time t;
HML_t is the return on the High minus Low portfolio at time t;
$\epsilon_{i,t}$ is the error term for the given stock at the given time.

Three-factor alpha

The exposure to each risk factor can be estimated through equation (2) using OLS. This can again be done for both individual stocks and entire portfolios of stocks. Furthermore, if it can be assumed that the portfolio's average risk exposure to each factor will remain at a reasonably stable level, then α_i can be interpreted as the 3-factor alpha of portfolio i. This can be seen as the 3-factor equivalent of Jensen's alpha, and measures the portfolio's performance adjusted for all three risk factors (Carhart, 1997). Where β failed to fully capture the covariance in stock returns (Fama & French, 1992), it is inherent that Jensen's alpha (Jensen, 1968) will absorb some of this unexplained covariance, caso quo risk, effectively undermining its value as a measure for risk-adjusted return. However, the factors of the 3-factor model do a better job at capturing covariance in stock returns than the single market factor from the CAPM. Therefore, 3-factor alpha is superior over Jensen's alpha in measuring return in excess of risk premia. Throughout the rest of this paper, 3-factor alpha and risk-adjusted return will therefore be used as synonyms.

2.3 Value strategies

In section 2.1, the Efficient Market Hypothesis (Fama, 1970) and its implications were discussed. One of its implications is that fundamental analysis could not yield positive abnormal returns and risk-adjusted returns. Graham and Dodd (1934), however, argue that fundamental analysis is the best and least risky method for stock selection. They differentiate between "speculative" and "analysis" methods for stock picking. Speculative is based on technical market factors such as past return, on manipulative factors as newspapers and analysts and on psychological factors like emotion. Analysis, on the other hand, is based on intrinsic factors of value such as earnings, assets, capital structure and dividend. They advise the use of analysis instead of speculation, as this is the safest and most prudent way to ensure profit on the capital market. In *The Intelligent Investor,* Benjamin Graham introduces the use of a firm and sound framework based on intrinsic value metrics and sensible theory (Graham & Zweig, 2003). He urges to always stick to the framework and never let emotion influence a decision. In his book, he presents such a framework based on value factors that investors can use. These works by Graham and Zweig (2003) and Graham and Dodd (1934) are still the basis for many investment strategies and frameworks that work on the basis of intrinsic value. It is therefore, that Benjamin Graham is often considered to be the founding father of value investing.

2.3.1 Value strategies in practice

One of the most evident proofs of the practical success of value investing, is Warren Buffet's investment vehicle Berkshire-Hattaway (Frazzini, Kabiller & Pedersen, 2013). Buffet, who said that Graham's *Intelligent Investor* is the best book on investing ever written, is known to be an avid backer of investing on the basis of intrinsic value measures. In addition, he has an excellent track record of high returns and beating the market over a prolonged period of time.

Frazzini et al. (2013) show that these returns cannot be fully explained by the Fama and French (1993) 3-factor model. To find out whether the positive risk-adjusted returns are truly the product of Buffet's stockpicking skill, two new factors are added to the model. These new factors are named Betting-Against-Beta and Quality-Minus-Junk, and function as proxies for the investor's skill in stock picking and portfolio formation. They largely cover the remaining variation in Buffet's returns. In addition, Frazzini et al. claim that controlled leverage[8] is used to boost returns. They conclude therefore that the good track record of Berkshire-Hattaway is not merely a product of luck, but the result of skillful stock selection and controlled risk-taking, thus confirming that prudently using a value approach to investing can actually generate positive risk-adjusted returns.

2.3.2 Value strategies in academic research

The success of investing in value stocks is also shown by Lakonishok, Shleifer and Vishny (1994). They form portfolios for every decile on several value ratios including book-to-market, earnings-to-price and cashflow-to-price. The stocks with the lowest ratios are called "glamour" stocks, and

[8] Leverage is an easy way to increase risk to a certain desired level

the ones with the highest ratios "value" stocks. They then show that on average, the value stocks generate higher returns than the glamour stocks on annual basis, and that they barely ever underperform the glamour stocks. Based on this, the conclusion is drawn that value stocks do on average earn a higher return than glamour stocks without being riskier.

Lakonishok et al. (1994) suggest that this effect may be due to extrapolation of the past into the present. Investors overestimate the future growth rate of stocks that have performed well in the past. This leads to a price run-up, and thus a lower book to market ratio, which is a characteristic of glamour stocks. Stocks that did badly, on the other hand, run out of favor and stay out of favor for too long. As the market price goes down, the book to market ratio goes up, and the stock becomes a value stock. In the long run, however, the market will recognize the extrapolation and the prices will adjust to the stocks' fair values. This leads to opportunities for smart investors that can spot the difference between value and glamour stocks early on. Buying the out-of-favor value stocks would likely earn them high returns as the market turns, without being notably more risky. Hence, this strategy is defined as contrarian investment by Lakonishok et al. (1994).

However, Fama and French (1995) show that high book to market ratios (high factor loading on HML) are accompanied by poor earnings over a prolonged period of time. In contrast, firms with low book-to-market (low or negative loadings on HML) show high earnings. Moreover, Fama and French (1996) are able to almost completely explain the anomalous returns on the Lakonishok et al. (1994) value portfolios with their 3-factor model. . In addition, Davis, Fama and French show that the value premium is largely explained by the 3-factor model. The newly introduced factors based on size and book-to-market seem to do a good job in covering the returns of the value stocks. In addition, it is shown by Fama and French (1996) that the SMB and HML portfolios have negative returns just as often as the market. This leads Fama and French (1996) to argue that the stocks picked by Lakonishok et al. are actually stocks in distress. The higher premia on these stocks are justified by a higher risk exposure. This means that the stocks picked on the basis of value metrics are actually not undervalued, but fundamentally riskier.

2.3.3 The magic formula

One of the latest additions to the spectrum of value strategies, is the magic formula (Greenblatt, 2006). It can be seen as a simplified version of one of his hedgefund's strategies, so that it is easy to implement for retail investors. Greenblatt argues that, in line with Graham and Zweig (2003), it would be intelligent to buy good stocks at a low price. To find such stocks, they must meet two criteria. First of all, they must be stocks from quality firms. Secondly, they must be cheap. Therefore, all stocks are ranked on their return on invested capital as a quality metric. Simultaneously, they are ranked on Earnings Yield as a value metric. These ranks are then added, and the firms with the lowest sum of ranks are selected into a portfolio. Every stock is held for exactly a year, before new stocks are selected. This would have amounted to an average annual return of over 30 percent from 1988 to 2004, according to Greenblatt.

Academic results by Novy-Marx (2013, 2014) are a bit more modest. He tests, among other strategies, the magic formula from mid-1963 to end-2012 on stocks from the Russell 1000 (largecap) and Russell 2000 (smallcap) indices. Nonetheless, he shows that Greenblatt's strategy would have returned a gross[9] average excess return of 8.15 and 11.2 percent on the largecap and smallcap portfolios respectively (Novy-Marx, 2014). This equals a statistically significant positive abnormal returns of 2.75 percent for both largecap and 4.68 percent for smallcap, but the strategy does not produce significant 3-factor alphas.

However, it is shown by Novy-Marx (2013) that the stocks that are ranked the worst, that is the stocks with the highest sum rank, have negative significant 3-factor alphas of over 2 percent, indicating these stocks earn less than would be justified by their exposure to 3-factor risk. Therefore, forming a long minus short (long-short, or L-S) portfolio might be a good idea. A long-short portfolio finances the long positions in the good stocks by short positions in the bad stock. It thus requires no capital from the investor to be formed. In addition, the exposure to the market factor would expectedly be around zero. This is an attractive trait for some investors, as it poses an excellent diversification opportunity to reduce portfolio risk.

Indeed, it is shown that such a L-S portfolio would typically have a statistically significant 3-factor alpha of about 3 percent (Novy-Marx, 2013) . However, there is no premium received for bearing market risk as beta is approximately zero[10]. Consequently, the excess returns are somewhat lower than those on the long-only portfolio, around 3.6 percent per annum for largecaps, and 5.9 percent for smallcaps.

[9] Novy-Marx (2013) uses the term gross excess return for the portfolio return in excess of the risk-free rate (equivalent to excess return in this paper), and net excess return for gross excess return minus transaction costs.

[10] Novy-Marx (2013) originally finds negative betas on the long-short portfolios as well, but creates beta-hedged long-short portfolios to achieve market exposures that approximate zero.

3. Data & Methodology

This section commences by discussing the various data sources that have been used and by describing the data. It then continues to explain the various methods and techniques that have been incorporated in the analysis of the magic formula.

3.1 Data

This paper evaluates the performance of the magic formula from June 1st, 1996 to May 31st, 2017. In order to investigate whether the results differed before and after the publication of Greenblatt's formula in 2006, the sample has been split into two ten-year parts. The first period spans June 1996 to May 2006, and the second period spans June 2007 to May 2017.

As a stock universe, the Russell 3000 has been selected as it covers over 90% of the American stock market in capitalization. The Russell 3000 index consists of the Russell 1000 (1000 largest firms in terms of market capitalization) and the Russell 2000 (the consecutive 2000 firms in terms of market capitalization). In this paper, the Russell 1000 index has been used as largecap universe, and the Russell 2000 as smallcap universe, following Novy-Marx (2013, 2014). The constituent lists for each year were obtained through Bloomberg. All the accounting data over the fiscal years 1995 to 2016 has been retrieved from WRDS Compustat North-America. The stock return data from 1996 to 2017 was taken from the CRSP database. The monthly factors for the three-factor model were downloaded from Kenneth French' website[11]. The classic research factors based on six portfolios[12] have been used.

For this paper, the Total Monthly Return, Return On Invested Capital (ROIC) and Earnings Yield are the most relevant. Monthly return is used to calculate the portfolio returns. ROIC measures the Earnings Before Interest and Taxes (EBIT) to the Tangible Capital, and functions as a proxy for quality. Earnings Yield proxies for value, and is defined as EBIT to Enterprise Value. The definitions of Tangible Capital and Enterprise Value can be found in Table 1, and are in line with Novy-Marx (2013).

According to Greenblatt (2006), Earnings Yield is superior to just using earnings to price ratio because it disregards differences in tax rates and capital structures, which are argued to be irrelevant. ROIC is better than Return On Assets (ROA), as it corrects for intangible assets and working capital. By the nature of these quality and value metrics, they do not work well for financials. The reason for this is, first of all, that most financial firms mainly have intangible capital

[11] Retrieved on 30 June 2017 from:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[12] As described in Section 2.2.2

Variable	Mean	Std. Dev.	Median	p25	p75	Defined as:
Monthly Total Return	1.039	16.009	0.661	-6.226	7.471	Monthly Total Return (RET in CRSP)[1] *in percentages (%)*
Earnings Yield[2]	-0.482	523.815	6.401	2.652	9.322	EBIT to Enterprise Value *(%)*
ROIC[2]	15.145	1214.030	11.437	4.354	21.525	EBIT to Tangible Capital *(%)*
EBIT	420.792	1822.135	61.979	14.225	234.532	Earnings before interest and taxes (EBIT) *in millions US dollar (mil. USD)*
Enterprise Value	6201.039	21663.461	1065.260	393.548	3592.829	Market Value + Long + Short Term Debt + Preferred Equity - Cash *(mil. USD)*
Tangible Capital	3189.127	12495.342	524.994	182.769	1828.200	PPE + Working Capital *(mil. USD)*
Market Value	5542.742	21284.875	908.368	345.309	2961.000	Common Shares Outstanding (CSHOM) * Share Price (PRCCM) *(mil. USD)*
Long Term Debt	1017.018	3272.513	121.246	1.197	611.018	Long term debt (DLTT) *(mil. USD)*
Short Term Debt	158.050	749.937	4.053	0.000	40.214	Debt in current liabilities (DLC) *(mil. USD)*
Preferred Equity	16.921	144.068	0.000	0.000	0.000	Redemption value of preferred equity (PSTKRV)[3] *(mil. USD)*
Cash	425.720	2105.611	77.378	25.383	228.677	Cash and short term investments (CHE) *(mil. USD)*
PPE	2771.808	12178.948	325.016	77.453	1334.439	Property, plant and equipment (PPEGT) *(mil. USD)*
Working Capital	417.319	1986.121	121.621	40.626	335.523	Working Capital (WCAP) *(mil. USD)*

Table 1 – Descriptive statistics and definitions of the variables of interest

This table shows the variables of interest for this paper. For every variable, the mean, standard deviation, median, first quartile (p25) and third quartile (p75) are presented. In addition, the definition of each variable is provided. For every used variable that was obtained directly through CompuStat (or CRSP for Monthly Total Return), the CompuStat variable name is given in capitals and parentheses. Finally, the units in which the variable is expressed are in italics and parentheses.

[1] If (RET) was unavailable through CRSP, and (TRT1M) from the CompuStat database was available, (TRT1M) was used.

[2] These variables have been calculated in consistency with Novy-Marx (2013, 2014).

[3] In line with Novy-Marx (2013, 2014), if PSTKRV was unavailable, liquidating value (PSTKL) was used if available, else carrying value (PSTK).

such as human capital on their balance sheets, effectively overstating their quality when measured through ROIC. Secondly, the accounting standards for reporting are different for financials, resulting in many missing values. Therefore, all observations with one-digit SIC-code of 6 have been excluded from the stock selection universe, following Novy-Marx (2013).

The descriptive statistics and the definitions of the variables of interest for this paper are stated in Table 1. The most striking are the extreme values that Monthly Return, Earnings Yield and ROIC can take, which are illustrated by their large standard deviations with regards to their quartile values. For Monthly Return, this seems to be caused by some observations well exceeding a return 100 percent in a given month. These seem however to correspond to the stocks real returns in the given month. In addition, the effect of outliers is largely if not fully eliminated by only using portfolio returns in the regressions.

The extreme values in ROIC are mostly caused by firms characterized by a negative working capital that is almost as big as the value of their Property, Plant and Equipment. The outliers in Earnings Yield are mostly due to firms holding very large cash amounts in relation to their market value. However, this poses no threat to the consistency of the estimators, as these variables are only used to rank the firms and form portfolios.

3.2 Methodology

3.2.1 Portfolio formation

Before stocks can be assigned to certain portfolios, they must be ranked on ROIC and Earnings Yield. Ranking is carried out annually. The firm with the highest Earnings Yield is assigned rank 1, the runner-up highest is assigned 2, and so on. The same method applies to the ROIC rank. Per evaluation period and per evaluation metric, three ranks are assigned. First, the entire sample is ranked. Secondly, separate ranks are assigned for the subsamples, one for the Russell 1000 and one for the Russell 2000. This enables to test for differences between large- and smallcaps.

In the special case that both EBIT and enterprise value or EBIT and tangible capital are negative, the calculated value for ROIC or Earnings Yield would be positive, as it is the product of two negatives. This would lead to undesirable results in the ranking procedure, therefore these stocks are excluded from ranking.

In order to test the magic formula, annual portfolios are formed in majorly the same fashion as Greenblatt (2006) proposes. The firms with the lowest (highest) sum of value and quality ranks are selected into a long side (short side) portfolio. The long side portfolio contains all the stocks that should be bought, whereas the short side portfolio contains the stocks that should be sold short. Long-short portfolios are formed by subtracting the short side form the long side. This results in nine Greenblatt portfolios per period, three for the entire sample and three for each market capitalization.

To also be able to perform tests on the value- and quality metric individually, single sort portfolios were formed on the basis of the respective rank. Again, three portfolios per period, per sample are created for both evaluation measures. This results in a grand total of 27 portfolios per period.

Every portfolio consists of 100 stocks, as this number is large enough to allow enough diversification but small enough for the stock selection to stay effective and to keep the transaction costs down, which may be important for some practical applications. In this study, however, transaction costs will be discarded, as they become more and more marginal with the rise of cheap online brokerage firms, and traditionally become relatively lower when more money is invested.

The portfolios are rebalanced annually on the first of June[13]. The possibility of a look-ahead bias has been eliminated[14] by only using accounting data from firms that had their fiscal year-end before December 31st. So in effect, all the data that has been used for the portfolio selection of 1996 was published somewhere in 1995, all the data for 1997 was made available in 1996, and so forth. The portfolios using ex-post data were formed in the same fashion except that accounting data was used for the current fiscal year, instead of for the most recent full fiscal year. So in effect, the ex-post portfolio for 1996 was formed using data that was published somewhere in 1996, and so on.

3.2.2 Research methodology

To transform monthly gross returns for a stock i into annual gross returns, equation (3) was used, where m denotes the portfolio month, so $m = 1$ for June, $m = 2$ for July, … , and $m = 12$ for May.

$$AnnualReturn_i = \left(\left(\prod_{m=1}^{12}\left(1 + \frac{MonthlyReturn_{(i,m)}}{100}\right)\right) - 1\right) * 100 \tag{3}$$

The gross annual returns for a given portfolio were calculated as the equal weighted average of the gross annual returns of all the stocks in that portfolio. The monthly portfolio returns were calculated in the same way, using the equal weighted average of all the monthly returns in that portfolio for that month. This is in line with Greenblatt's (2006) proposition of equal weighted portfolios, as opposed to the value weighted portfolios used by Novy-Marx (2013, 2014).

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[13] This is largely consistent with Novy-Marx (2013, 2014) where the portfolios are rebalanced annually at the end of June.

[14] Eliminated, because the SEC requires the annual report to be reported within 90 days of the fiscal year-end, and all firms in the sample are subject to this regulation.

The Jensen alpha measure is estimated as the intercept of the CAPM (equation (1)) through an OLS regression. The 3-factor alpha is estimated as the intercept in the Fama and French (1993) 3-Factor model (equation(2)) through an OLS regression. With regards to the Jensen alpha's and the 3-factor alpha's assumption of reasonably stable risk exposures over time, it is expected that this assumption is met. The magic formula annually picks stocks according to a systematic framework, expectedly resulting in more or less the same types of stocks in each portfolio at every time. Hence, the factor exposures should be reasonably stable over time. All OLS regression results and according t-stats and p-values have been obtained using White (1980) heteroskedasticity-robust standard errors.

The alphas and excess returns were annualized by multiplying the monthly value by 12. Examples of this widely used method include Carhart (1997) and Brown, Fraser and Liang (2008). The standard deviation of the excess return was annualized by multiplying it by the square root of 12, in line with Sharpe (1994).

To calculate the Sharpe ratio, first the average monthly excess return $\overline{D_i}$ for portfolio i is calculated through (4) over the months $t = 1$ through to $t = T$. Then, the Standard Deviation σ_{D_i} of the monthly gross excess returns is calculated through (5). Finally, the formula for the monthly Sharpe ratio is given by (6) and it becomes clear that the annualized Sharpe ratio is calculated through equation (7), in line with Sharpe (1966, 1994). The average excess returns are multiplied by 12, and consequently their standard deviation has to be multiplied by the square root of 12 for the ratio to stay consistent[15].

$$\overline{D_i} = \frac{1}{T}\sum_{t=1}^{T}(R_{i,t} - R_{f,t}) \tag{4}$$

$$\sigma_{D_i} = \sqrt{\frac{\sum_{t=1}^{T}\left((R_{i,t} - R_{f,t}) - \overline{D_i}\right)^2}{T-1}} \tag{5}$$

$$SharpeRatio_i = \frac{\overline{D_i}}{\sigma_{D_i}} \tag{6}$$

$$AnnualizedSharpeRatio_i = \frac{12}{\sqrt{12}} * \frac{\overline{D_i}}{\sigma_{D_i}} \tag{7}$$

[15] To effectively annualize the standard deviation, the sum of squared errors $\sum_{t=1}^{T}\left((R_{i,t} - R_{f,t}) - \overline{D_i}\right)^2$ has to be multiplied by 12, which equals multiplying the standard deviation itself by the square root of 12.

4. Results

In this section, all results from analysis of the magic formula will be presented and discussed. Moreover, they will be linked to economic theory and previous research as much as possible. In the first part of this section, the magic formula will be tested on its predictive qualities. The behavior of gross returns of the magic formula, ROIC and EY on annual basis are discussed. Subsequently, a light will be shed on the risk-adjusted performance of the magic formula, analyzed on a monthly basis. In the second part of this section, the descriptive value of the magic formula is shown, which turns out to be extraordinary. In the last part of this section, the performance of the magic formula will be compared before and after its publication in 2006.

4.1 Predictive power of the magic formula

The target of the magic formula is to predict which stocks will generate more returns than others on the basis of current accounting data. Therefore, this section will analyze the performance of the magic formula when portfolios are formed using accounting data that was already publicly available at the time of portfolio formation, as described in section 3.2.1.

4.1.1 Gross portfolio returns

When evaluating the magic formula on simple portfolio returns over the holding period of one year, the magic formula seems to perform quite well over the last 21 years. The simple average return over the portfolio holding periods was 12.23 percent, against 7.75 percent average return on the Russell 3000 over the same periods. The spread between the long- and short side is, on average, 7.69 percent. The quality metric ROIC does almost as good as the magic formula for all three portfolios. The value metric, Earnings Yield, produced similar returns on the long portfolio. However, the bottom-ranked stocks on Earnings Yield earn on average more than the bottoms of ROIC and the Magic Formula, thus creating smaller spread between the top- and bottom ranked stocks and returning less on the long-short portfolio (Table 2).

Most striking are the negative returns of the long side portfolio during the rise of the dot-com bubble (1998/1999), and the remarkably strong positive returns during the collapse of the same bubble (2000/2001). This is in part consistent with Greenblatt (2006). He shows strong positive returns on his portfolio throughout the entire dot-com bubble, contrarian to this paper, where only the portfolio periods starting in 2000 and 2001 are positive. This is nonetheless remarkable, as the Russell 3000 had negative returns of over 10 percent in both periods. The short side portfolio, on the other hand, shows opposite behavior to the long side, resulting in large negative

	Magic Formula			ROIC			Earnings Yield			Russell 3000
Portfolio year[1]	Long-side	Short-side	Long - Short	Long-side	Short-side	Long - Short	Long-side	Short-side	Long - Short	VW Index return
1996	12.03	-21.49	33.52	7.04	-21.33	28.37	6.78	-18.66	25.44	22.44
1997	14.72	9.68	5.04	24.54	4.27	20.27	20.77	9.52	11.25	27.71
1998	-10.43	17.59	-28.03	-0.40	40.33	-40.73	-10.58	10.80	-21.39	16.59
1999	-9.67	53.58	-63.25	0.13	49.94	-49.81	-3.66	59.93	-63.59	10.45
2000	55.17	-47.03	102.20	30.74	-46.41	77.15	37.15	-35.28	72.43	-10.77
2001	21.70	-45.35	67.05	9.03	-42.60	51.63	22.75	-23.38	46.13	-13.66
2002	-12.58	9.44	-22.02	-6.45	8.48	-14.93	-15.19	4.51	-19.70	-9.40
2003	41.11	47.26	-6.14	27.01	40.35	-13.34	51.07	52.02	-0.95	17.70
2004	10.57	-23.21	33.78	13.60	-23.49	37.09	18.04	-15.74	33.78	7.55
2005	17.85	19.08	-1.24	8.79	17.01	-8.22	26.01	25.40	0.61	8.18
2006	23.91	3.34	20.57	20.85	1.33	19.52	32.40	8.29	24.11	20.43
2007	-19.85	-22.44	2.59	-17.00	-22.85	5.85	-11.11	-21.00	9.89	-8.32
2008	-30.98	-30.07	-0.91	-29.43	-29.73	0.30	-28.51	-30.92	2.41	-34.53
2009	42.35	56.90	-14.55	33.13	36.81	-3.68	56.65	66.32	-9.68	20.81
2010	28.32	21.44	6.88	30.64	32.40	-1.76	20.24	22.23	-1.99	24.72
2011	-10.01	-22.53	12.51	-3.36	-20.51	17.15	-8.97	-25.35	16.37	-3.86
2012	37.07	40.66	-3.59	34.69	34.21	0.49	29.55	42.84	-13.29	25.22
2013	28.27	24.75	3.51	22.24	29.11	-6.87	18.70	30.30	-11.60	18.27
2014	10.87	27.37	-16.50	17.22	23.37	-6.15	1.61	17.94	-16.33	9.77
2015	-5.08	-25.85	20.77	-2.70	-27.89	25.19	-12.69	-19.35	6.66	-1.83
2016	11.43	2.13	9.30	13.39	2.02	11.37	17.28	3.80	13.48	15.36
Average	12.23	4.54	7.69	11.13	4.04	7.09	12.78	7.82	4.96	7.75

Table 2 – Return percentages for the magic formula, ROIC and Earnings Yield, per portfolio, per portfolio holding period

This table shows the gross returns over each portfolio holding period in percentage on the long side, short side and long minus short portfolios formed on ranking procedures based on the magic formula, Earnings Yield and ROIC. The last column shows the gross returns over the same period on the Russell 3000 value weighted index. The average return is the simple average of the gross annual return percentages for the given portfolio.

[1] The portfolio holding periods all exactly stretch one year, but the portfolio years do not convey to normal years. The portfolios are formed on the first trading day of June, and held through to the last trading day of May in the next year. Thus, the 1996 portfolio return is generated from June 1996 to May 1997.

returns on the long-short portfolio during the rise, and tremendous positive returns on the long-short portfolio during the collapse of the dot-com bubble.

4.1.2 Risk-adjusted performance

When evaluating the magic formula in terms of risk and reward, the Sharpe ratios found by Novy-Marx (2013) are very similar to those in this study (except for the long-short portfolios), and are especially high for the long side portfolios. They even come close to the Sharpe ratio of Berkshire-Hattaway (Frazinni et al., 2013), one of the best performing mutual funds in the field. The difference in Sharpe Ratios on the long-short portfolios is most likely caused by the difference in volatility on the short side between Novy-Marx (2013) and this study.

However, where the average annual returns and Sharpe ratios may seem quite high, the largecap abnormal return, despite being of the right sign, is only statistically significant when evaluated at a 10 percent significance level (Table 3). In comparison to Novy-Marx (2014), this paper finds slightly larger Jensen alphas in the largecap universe, but Novy-Marx' are more robust in statistical sense. Furthermore, Novy-Marx' abnormal returns are net of transaction costs, which may explain the difference in magnitude. A possible explanation for the difference in statistical robustness of the alphas is the difference in sample period, as Novy-Marx' sample stretches almost 50 years (from 1963 to 2012), in contrast to this paper's 21 years.

Finally, the 3-factor alphas are insignificant over the entire range of portfolios. This means that although the magic formula may be profitable, these profits are justified by exposure to the systematic risk factors of the Fama and French (1993) 3-factor model. For the long side portfolios, this is in line with Novy-Marx (2013, 2014), where no significant 3-factor alphas are found either. For the other portfolios, however, this is inconsistent with Novy-Marx (2013), where significant 3-factor alphas are found for the short and long-short portfolios in both market capitalizations.

Anomalies in the smallcap universe

Especially for the smallcaps, the results deviate from those found in other studies. The empirical evidence in Table 3 shows that the smallcaps underperform the largecaps in excess return and Jensen's alpha, and also that the long side smallcaps do worse than the short side smallcaps, although the latter reverses when correcting for the internet bubble. These results are inconsistent with the results found by Novy-Marx (2013, 2014). Novy-Marx finds in both studies that deploying the magic formula is just as profitable, if not more, than among largecapss. In addition, Novy-Marx (2013) finds a significant positive 3-factor alpha on the long-short portfolio, and a significant negative alpha on the short portfolio.

	Long side		Short side		Long - Short		Russell 3000
	Large	Small	Large	Small	Large	Small	EW Index
Annualized $(R_i - R_f)$	14.495***	20.649***	3.337	5.147	9.001*	13.345*	10.149**
	(3.92)	(4.56)	(0.46)	(0.55)	(1.77)	(1.86)	(2.15)
Annualized Std. Deviation	16.949	20.762	33.524	42.937	23.253	32.942	21.624
Annualized Sharpe Ratio	0.86	0.99	0.10	0.12	0.39	0.41	0.47
Annualized Jensen's Alpha	7.655***	12.917***	-9.278**	-8.184	14.760***	18.928***	1.241
	(4.21)	(4.79)	(-2.30)	(-1.23)	(3.45)	(2.88)	(0.61)
Annualized 3-factor Alpha	6.410***	10.557***	-9.973***	-7.409	14.222***	15.806***	-0.138
	(4.04)	(5.79)	(-2.58)	(-1.37)	(3.59)	(2.80)	(-0.10)
Beta	0.979***	1.009***	1.672***	1.564***	-0.692***	-0.553***	1.169***
	(23.15)	(27.13)	(16.69)	(15.14)	(-6.71)	(-4.90)	(33.92)
HML	0.339***	0.529***	0.086	-0.495***	0.250**	1.020***	0.275***
	(4.96)	(8.23)	(0.61)	(-2.95)	(2.00)	(6.26)	(4.48)
SMB	0.076	0.729***	0.576***	1.414***	-0.497***	-0.683***	0.602***
	(1.03)	(6.50)	(4.16)	(7.03)	(-4.52)	(-2.90)	(7.52)
N	252	252	252	252	252	252	252
adj. R-sq	0.818	0.842	0.708	0.643	0.376	0.348	0.907

Table 3 – Performance of the magic formula

All results in the table have been obtained using monthly return data and monthly research factors. The dependent variable is monthly portfolio return, and all variables are in percentages. The Russell 3000 EW Index is the equal-weighted return for the Russell 3000, calculated as the sample mean. Annualized $R_i - R_f$ is the is the annualized excess return (the same as gross excess return in Novy-Marx (2013, 2014)). N is the number of observations used in calculation and estimation, and adj. R-sq is the adjusted R^2 measure for the 3-factor model regression. In parentheses are the White (1980) heteroskedasticity-robust t-statistics.

*p<0.1 **p<0.05 ***p<0.01

4.1.3 The factor loadings and their meaning

In this subsection, a more thorough analysis of the composition of each of the portfolios is presented. To identify which type of stocks are selected for each portfolio, it can be very informative to look at their factor loadings. The factor loadings can for instance tell whether and how a group of stocks is prone to market movements, or if the firms are likely to be in relative distress.

The first of the factor loadings is the β, or exposure to market risk. The long side stocks have β-loadings of around one, signaling a one-on-one exposure to market risk. The short side stocks, however, load much higher on β. Both large- and smallcap portfolios have a Beta of around 1.6, indicating quite high exposure to market risk. The long-short portfolio loads negatively on β, as the short side overcompensates for the β exposure of the long side. This is consistent with the β's found by Novy-Marx (2013, 2014), with exception for the long-short β's, which are close to zero due to the practice of β-hedging in Novy-Marx' work. The index β's are marginally larger than one, as the market index is equal-weighted, resulting in heavier weights of the smallcaps which traditionally have slightly higher β's.

Continuing with the other factors, the long side portfolios load strong and positive on HML. This typical for firms with high book to market ratios (Fama & French, 1996) and signals persistently low earnings (Fama & French, 1995). Moreover, Fama and French (1997) argue that a similar loading is typical for industries in a bad time of the economic cycle. The contrary is true for the short side, suggesting these portfolios to consist of firms with persistently high earnings and from industries that are in a good economic state. This confirms the presumption that the magic formula is a value strategy as described by Lakonishok et al. (1994): contrarian investment.

As expected, the Russell 2000 portfolios load much stronger on SMB than the Russell 1000 portfolios. This is of course partly because the Russell 2000 consists mainly of firms with relatively small market capitalizations. Investing in smaller firms is generally considered to be more risky, and therefore an extra premium is demanded. Nonetheless, the SMB loadings for the short side are still considerably higher than those of the long side, when comparing within the same stock universe, although the magnitude of the difference is larger for the smallcaps.

In general, it seems thus that the long side of the magic formula mainly selects larger firms with normal market risk exposures, that are relatively distressed. The short side, on the other hand, consists of smaller stocks with more volatile prices. However, the latter group of firms is also likely to be characterized by persistently high earnings and has a high probability of being in an industry in good economic state.

This results in a long-short portfolio with interesting risk features. First of all, the negative Beta-loading may be very interesting for some investors, as it creates the possibility of adding an anti-cyclical investment, which can be used to hedge against market risk. In years of negative market return, this would pose some kind of insurance, for example during crisis years as 2000, 2001 and 2008 (Table 2). The negative SMB loading creates another hedging possibility, especially interesting for a portfolio with a large proportion of smallcaps. Lastly, the long-short portfolio creates an opportunity to invest in relative distress risk, as it has a very strong positive loading on HML. This may be appealing to certain investors, as it is sometimes argued that the premium on distress risk is irrationally high and therefore comes close to an arbitrage possibility (Lakonishok et al., 1994; Haugen, 1995).

When comparing the factor loadings from this study to those found on the long portfolios by Novy-Marx (2014), it is striking how similar they are. They are almost a one-on-one copy on both sign and magnitude for all three factors β, HML, and SMB. Unfortunately, for the short portfolio and the long-short portfolio, no 3-factor model factor loadings for SMB and HML compatible with those used in this study are printed by Novy-Marx (2013, 2014).

In conclusion, there are some signs that investing according to the magic formula may actually be quite profitable, especially in the largecap universe. The significant (t = 2.78) positive excess return of 11.26 percent per annum is also a promising token (Table 3). However, none of the annualized 3-factor alphas on any of the portfolios is statistically significant, and neither are the Jensen alphas. Moreover, the factor loadings on the long portfolios of the magic formula show factor loadings corresponding with persistently lower earnings and firms in relative distress. It is thus the most likely that the excess returns of the magic formula are so high because of risk, which is in line with the efficient market hypothesis (Fama, 1970).

4.2 Descriptive power of the magic formula

Although not proven to be any good as a predictive measure of steady and strong risk-adjusted stock returns, the magic formula does an excellent job in when used as a descriptive measure of quality and value, using ex-post data as described in section 3.2.1.

The magic formula as it is shown in the previous sections and as it was proposed by Greenblatt in his book (2006), makes use of a stock selection process on the basis of publicly available accounting data over the last full book year available. However, Greenblatt points out in the same book (2006) that this is actually a simplified version of the stock selection procedure that his own hedge fund uses, namely on the basis of forecasted instead of public accounting data. Therefore, it would be interesting to see how well the strategy performs if it is based on accounting data over the actual year in which the portfolio is held. It is important to stress that a similar portfolio could never be formed in practice, as the data that is used in the stock selection process only became publicly available during or immediately after the portfolio holding period. Nonetheless, the results are of great scientific value (Table 4).

	Long side		Short side		Long - Short		Russell 3000
	Large	Small	Large	Small	Large	Small	EW Index
Annualized $(R_i - R_f)$	14.495***	20.649***	3.337	5.147	9.001*	13.345*	10.149**
	(3.92)	(4.56)	(0.46)	(0.55)	(1.77)	(1.86)	(2.15)
Annualized Std. Deviation	16.949	20.762	33.524	42.937	23.253	32.942	21.624
Annualized Sharpe Ratio	0.86	0.99	0.10	0.12	0.39	0.41	0.47
Annualized Jensen's Alpha	7.655***	12.917***	-9.278**	-8.184	14.760***	18.928***	1.241
	(4.21)	(4.79)	(-2.30)	(-1.23)	(3.45)	(2.88)	(0.61)
Annualized 3-factor Alpha	6.410***	10.557***	-9.973***	-7.409	14.222***	15.806***	-0.138
	(4.04)	(5.79)	(-2.58)	(-1.37)	(3.59)	(2.80)	(-0.10)
Beta	0.979***	1.009***	1.672***	1.564***	-0.692***	-0.553***	1.169***
	(23.15)	(27.13)	(16.69)	(15.14)	(-6.71)	(-4.90)	(33.92)
HML	0.339***	0.529***	0.086	-0.495***	0.250**	1.020***	0.275***
	(4.96)	(8.23)	(0.61)	(-2.95)	(2.00)	(6.26)	(4.48)
SMB	0.076	0.729***	0.576***	1.414***	-0.497***	-0.683***	0.602***
	(1.03)	(6.50)	(4.16)	(7.03)	(-4.52)	(-2.90)	(7.52)
N	252	252	252	252	252	252	252
adj. R-sq	0.818	0.842	0.708	0.643	0.376	0.348	0.907

Table 4 – Performance of the descriptive (ex-post) magic formula:

This table shows the performance of the magic formula portfolios, when they are formed on the basis of accounting data that was published during the holding period, instead of before the holding period. All results in the table have been obtained using monthly return data and monthly research factors. The dependent variable is monthly portfolio return, and all variables are in percentages. The Russell 3000 EW Index is the equal-weighted return for the Russell 3000, calculated as the sample mean. The process of annualizing monthly values is further explained in section 3.2.2. Annualized $R_i - R_f$ corresponds with gross excess return in Novy-Marx (2013)). N is the number of observations used in calculation and estimation, and adj. R-sq is the adjusted R^2 measure for the 3-factor model regression. In parentheses are the White (1980) heteroskedasticity-robust t-statistics.

*p<0.1 **p<0.05 ***p<0.01

Where the factor loadings for the risk factors are all very similar[16] to those of the predictive portfolios in Table 3, it becomes immediately clear that their descriptive counterparts have much higher excess returns, that are furthermore robust for risk adjustment. A glimpse at Table 4 teaches us that the descriptive portfolios produce significant positve annualized risk-adjusted returns of 6.41 percent (t = 4.04) and 10.56 (t = 4.56) percent respectively on the largecap and smallcap long-only portfolios. On the short side, the annualized three-factor alphas are negative, and significant for the largecap portfolio. This is good news for the magic formula, as it is an indicator that the bad stocks are indeed performing worse than expected on the basis of their three-factor risk exposures, as opposed to the good stocks that actually perform better.

Indeed, the long-short portfolios also have large positive significant alphas, as they fully capture the spread between the good and the bad stocks, meanwhile bringing down risk exposures. It is also noteworthy how high the Sharpe ratios are on the long side, even to the point where every percent of standard deviation is compensated by one percent of excess return.

However, as pointed out before it will be impossible to form the portfolios described above in practice. The question arises if there are methods which could nonetheless approximate similar portfolios. The most easy way would be to first make estimates and forecasts of the accounting variables needed in the ranking process, as pointed out by Greenblatt (2006). This would of course still be extremely difficult and time consuming, making it virtually impossible to do for any private investor. Institutional investors have better chances. They often have larger research capacity and more advanced estimation techniques at their disposal. Nonetheless, it remains unclear whether the high returns are driven by investors that are actually expecting the firms to start doing better, or by the gradual release of positive information by the firm during the year, although both explanations would be sound with the hypothesis of efficient markets (Fama, 1970).

4.3 Persistence of the magic formula after its publication

With regards to the predictive version of the formula, the imminent question rises whether risk-adjusted returns of the formula are different before and after the publication of the Greenblatt's book in 2006, and if they will persist in the future. When evaluating the magic formula over the course of the entire sample period, there are no significant 3-factor alphas found and all variation in returns is explained by risk. However, it is a possibility that there are positive 3-factor alphas before the publication of the magic formula in 2006, and that they are evened out by negative alphas after the publication.

[16] So each of the portfolios consist of the same types of firms as their predictive counterparts, which are described in a detailed manner in Section 4.1.2

If the risk-adjusted returns have changed, it is to be expected on the basis of the efficient market hypothesis (Fama, 1970) that their effect has shifted forward in time after the first publication of Greenblatt's book in 2006. Hence, the predictive portfolios should return less, because much of the return associated with Earnings Yield and ROIC will already be priced in the market before portfolio formation takes place. To test whether this theory holds, it is expected that the return on predictive portfolios is lower from 2007 to 2016 (Appendix A, Table A2) than from 1996 to 2005 (Appendix A, Table A1).

When looking Tables A1 and A2 in Appendix A, one might get the impression that indeed the excess return on the predictive portfolios is lower after 2006 than before. However, this difference is not statistically significant (t = -0.27)[17] and is possibly due to differences in risk premia or risk exposures before and after 2006. Moreover, the effect actually reverses when controlling for the financial crisis years 2007 and 2008 (Appendix A, Table A3). In addition, the 3-factor alphas do barely change, and if they change they are increasing, both on long and long-short portfolios. What may, however, explain the differences in excess return before and after 2006, is the strong and statistically significant (t = -3.82)[18] change in the factor loading on HML. The loading is positive and significant before 2006, but approaches zero after 2006.

This is somewhat remarkable, as HML is traditionally the most important factor in explaining the value premium (Fama & French, 1996; Davis et al., 2000). A high factor loading to HML would therefore mean that a stock is a value stock, whereas negative factor loadings would signal glamour stocks. The empirical evidence thus suggests, that the stocks selected by the magic formula are truly value stocks before 2006, but are neither value nor glamour stocks after 2006. However, the HML loading for the equal weighted Russell 3000 index also greatly diminished after 2006. Therefore, the most likely explanation is that the found phenomenon is simply sample specific for the period after 2006.

Lastly, the formula fails to generate 3-factor alphas that are significantly different from zero both before and after 2006. Apparently, the high returns of the magic formula are explained by risk both before and after the publication of *The Little Book that Beats the Market* by Greenblatt (2006). These findings are consistent with the Efficient Market Hypothesis by Fama (1970). This implies that the magic formula yields no arbitrage opportunities. The high returns are justified by high risk exposures. Hence, the expectation is that the magic formula will generate portfolios with similar high risk exposures, caso qua high returns, in the future.

Another point of concern for the future of the magic formula, is that Greenblatt's own hedge fund, Gotham Capital, uses forecasts of Earnings Yield and ROIC to form portfolios. This identifies

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[17] White (1980) heteroskedasticity-robust t-stat for the difference in excess return on the largecap predictive long portfolio before and after 2006. Tests of the smallcap portfolio yields similar results

[18] White (1980) heteroskedasticity-robust t-stat for the difference in HML factor loading on the largecap predictive long portfolio before and after 2006 Tests of the smallcap portfolio yields similar results

a problem: the man who introduced the magic formula to the public, is likely to have exposure to the stocks that the simple version of the magic formula selects. Moreover, he has launched a publicly available website that actively generates a selection of stocks according to the principles of the magic formula (Greenblatt, 2006). These stocks are possibly already held by Gotham Capital. This means that if people start buying these stocks and create upward price pressure, Greenblatt might, through Gotham Capital, actually profit from his own investment advice. Investigations in this field are however outside the scope of this paper, and therefore left on the table for future research.

5. Conclusion

In this section, all conclusions drawn from the theoretical and empirical evidence will be presented. First and foremost, there is no unambiguous evidence that investing according to the magic formula is better than simply investing in the market index. Although it is true that over the last 21 years, the average return would have been about 4 percent higher than the market return, the empirical evidence suggests that this is merely the product of higher risk exposure. In fact, the long side portfolios are likely to largely consist of firms with persistently low earnings, firms in relative distress and firms from industries that are in a bad state of the economic cycle. The opposite is true for the short side portfolios. Besides, the latter tend to be made up of slightly smaller companies.

Nonetheless, the magic formula may have some value for prudent investors. The evidence shows that the spread between the good and bad stocks according to the magic formula is quite large. In addition, a long-short portfolio formed according to the magic formula manifests a special set of risk exposures, that may be very attractive to some investors. Besides, some investors solely care about absolute returns, not risk. For those, the magic formula might be a good investment framework.

Moreover, evidence is found that descriptive portfolios, formed by combining the ex-post values of Earnings Yield and ROIC, do remarkably well. In fact, these portfolios are shown to have annualized 3-factor alphas of 6.41 precent for the largecap long only portfolio, and 10.56 percent for the smallcap long-short portfolio. This provides strong evidence that Earnings Yield and ROIC are excellent proxies for value and quality, respectively, but that this is priced into the market right away or even before the information becomes publicly available.

When comparing the samples before and after the publication of the magic formula in 2006, this research finds a risk-based explanation of the high returns both before and after 2006. This is consistent with the hypothesis of efficient capital markets. No significant changes are found in excess returns, Jensen's alphas or 3-factor alphas before and after the publication. Surprisingly, the HML factor loading, linked closely to value premium, fell significantly after 2006. This is however most likely to be sample specific, as it appears that the market index also loads less strong on HML after 2006. With regards to the future of the magic formula, the high returns are expected to be persistent in the future, as they are justified by risk. The question remains, whether Greenblatt himself actually profits from the publication of the magic formula through his hedge fund's investments This could be further investigated in the future. In addition, new research could be focused on finding better ways to profit from the evident function of Earnings Yield and ROIC as proxies for value and quality.

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Appendix A

	Long side		Short side		Long - Short		Russell 3000
	Large	Small	Large	Small	Large	Small	EW Index
Annualized $(R_i - R_f)$	11.923**	9.842	3.653	10.440	4.715	-4.154	9.863
	(2.03)	(1.34)	(0.31)	(0.64)	(0.55)	(-0.36)	(1.40)
Annualized Std. Deviation	18.566	23.267	37.623	51.515	27.308	36.653	22.351
Annualized Sharpe Ratio	0.64	0.42	0.10	0.20	0.17	-0.11	0.44
Annualized Jensen's Alpha	6.734*	4.230	-7.090	-1.823	10.264	2.492	3.040
	(1.79)	(0.77)	(-1.03)	(-0.16)	(1.42)	(0.25)	(0.86)
Annualized 3-factor Alpha	0.097	-4.352	-7.333	0.487	3.860	-8.409	-2.133
	(0.03)	(-1.08)	(-1.02)	(0.05)	(0.57)	(-0.97)	(-0.78)
Beta	1.112***	1.093***	1.796***	1.692***	-0.684***	-0.599***	1.246***
	(17.35)	(16.01)	(10.34)	(10.23)	(-3.84)	(-3.68)	(24.21)
HML	0.649***	0.717***	-0.040	-0.518*	0.689***	1.235***	0.423***
	(5.67)	(5.81)	(-0.19)	(-1.76)	(3.48)	(5.06)	(5.22)
SMB	0.236***	0.932***	0.336**	1.418***	-0.095	-0.481*	0.607***
	(2.86)	(7.73)	(2.01)	(6.46)	(-0.70)	(-1.90)	(7.72)
N	120	120	120	120	120	120	120
adj. R-sq	0.734	0.747	0.662	0.672	0.409	0.497	0.872

Appendix A Table A1 – Performance of the magic formula before 2006:

All results in the table have been obtained using monthly return data and monthly research factors. The dependent variable is monthly portfolio return, and all variables are in percentages. The Russell 3000 EW Index is the equal-weighted return for the Russell 3000, calculated as the sample mean. Annualized $R_i - R_f$ is the is the annualized excess return (the same as gross excess return in Novy-Marx (2013, 2014)). N is the number of observations used in calculation and estimation, and adj. R-sq is the adjusted R2 measure for the 3-factor model regression. In parentheses are the White (1980) heteroskedasticity-robust t-statistics.

*p<0.1 **p<0.05 ***p<0.01

	Long side		Short side		Long - Short		Russell 3000
	Large	Small	Large	Small	Large	Small	EW Index
Annualized $(R_i - R_f)$	9.647	8.797	8.379	12.204	0.791	-3.884	10.382
	(1.57)	(1.22)	(1.00)	(1.13)	(0.20)	(-0.58)	(1.50)
Annualized Std. Deviation	19.383	22.832	26.439	34.010	12.434	21.247	21.859
Annualized Sharpe Ratio	0.50	0.39	0.32	0.36	0.06	-0.18	0.47
Annualized Jensen's Alpha	0.691	-1.248	-3.207	-0.654	3.391	-1.100	0.230
	(0.36)	(-0.40)	(-0.82)	(-0.09)	(0.89)	(-0.17)	(0.10)
Annualized 3-factor Alpha	1.029	-0.188	-3.716	-1.616	4.242	0.925	0.351
	(0.51)	(-0.09)	(-1.08)	(-0.27)	(1.23)	(0.15)	(0.28)
Beta	1.092***	1.053***	1.375***	1.465***	-0.279***	-0.409***	1.150***
	(24.09)	(20.65)	(17.77)	(10.43)	(-3.78)	(-3.13)	(34.90)
HML	0.113	0.367***	-0.099	-0.198	0.213	0.566**	0.085
	(1.41)	(5.00)	(-0.57)	(-0.77)	(1.50)	(2.39)	(1.43)
SMB	0.241**	0.943***	0.784***	1.297***	-0.543***	-0.354	0.800***
	(2.61)	(10.08)	(5.08)	(4.52)	(-3.55)	(-1.22)	(12.70)
N	120	120	120	120	120	120	120
adj. R-sq	0.887	0.914	0.833	0.658	0.282	0.119	0.961

Appendix A Table A2 – Performance of the magic formula after 2006

All results in the table have been obtained using monthly return data and monthly research factors. The dependent variable is monthly portfolio return, and all variables are in percentages. The Russell 3000 EW Index is the equal-weighted return for the Russell 3000, calculated as the sample mean. Annualized $R_i - R_f$ is the is the annualized excess return (the same as gross excess return in Novy-Marx (2013, 2014)). N is the number of observations used in calculation and estimation, and adj. R-sq is the adjusted R^2 measure for the 3-factor model regression. In parentheses are the White (1980) heteroskedasticity-robust *t*-statistics.
*p<0.1 **p<0.05 ***p<0.01

	Long side		Short side		Long - Short		Russell 3000
	Large	Small	Large	Small	Large	Small	EW Index
Annualized $(R_i - R_f)$	16.762***	15.550**	14.593*	15.369	2.083	0.094	16.796***
	(3.23)	(2.49)	(1.89)	(1.46)	(0.50)	(0.01)	(2.70)
Annualized Std. Deviation	14.683	17.650	21.884	29.794	11.888	19.573	17.603
Annualized Sharpe Ratio	1.14	0.88	0.67	0.52	0.18	-0.00	0.95
Annualized Jensen's Alpha	0.341	-2.775	-8.127*	-10.490	8.383*	7.629	-2.521
	(0.21)	(-0.92)	(-1.97)	(-1.35)	(1.89)	(1.08)	(-1.05)
Annualized 3-factor Alpha	0.830	-0.180	-6.037*	-7.146	6.782*	6.881	-0.478
	(0.49)	(-0.10)	(-1.69)	(-1.18)	(1.69)	(1.06)	(-0.50)
Beta	1.046***	0.964***	1.299***	1.343***	-0.253***	-0.380***	1.073***
	(26.52)	(25.43)	(15.10)	(10.40)	(-2.72)	(-2.85)	(52.31)
HML	0.097	0.246***	0.147	-0.178	-0.050	0.425*	0.091***
	(1.54)	(3.99)	(1.31)	(-0.73)	(-0.39)	(1.68)	(2.67)
SMB	0.114*	0.871***	0.751***	1.610***	-0.637***	-0.739***	0.787***
	(1.82)	(12.81)	(5.46)	(6.65)	(-4.43)	(-2.72)	(23.25)
N	96	96	96	96	96	96	96
adj. R-sq	0.906	0.928	0.842	0.693	0.343	0.183	0.982

Appendix A Table A3 – Performance of the magic formula after 2008 (excluding financial crisis)

All results in the table have been obtained using monthly return data and monthly research factors. The dependent variable is monthly portfolio return, and all variables are in percentages. The Russell 3000 EW Index is the equal-weighted return for the Russell 3000, calculated as the sample mean. Annualized $R_i - R_f$ is the is the annualized excess return (the same as gross excess return in Novy-Marx (2013, 2014)). N is the number of observations used in calculation and estimation, and adj. R-sq is the adjusted R^2 measure for the 3-factor model regression. In parentheses are the White (1980) heteroskedasticity-robust *t*-statistics.

*p<0.1 **p<0.05 ***p<0.01