The Discounted Cash Flow Terminal Value Model as an Investment Strategy

Danish Title: DCF-modellens terminalværdi som en investeringsstrategi

By
André Thormann (92081)
&
Henrik Foged Rasmussen (92770)

A thesis presented for the degree of Master of Science in Finance and Accounting (Cand.Merc.FIR)

Copenhagen Business School
Supervisor: Professor Thomas Plenborg
May 2019

Number of pages: 120
Number of characters: 270,175

Abstract

Når analytikere værdiansætter aktier, budgetterer de ofte flere år ud i fremtiden, selvom den værdi, der genereres i selve budgetperioden, udgør en lille del af den samlede værdiansættelse. Størstedelen af en virksomheds værdi bestemmes derimod i terminalperioden - en uendelig annuitet, der omfatter alle år efter budgetperioden. Litteraturen peger i retning af, at analytikernes budgetter er for optimistiske, og at deres antagelser for terminalperioden ikke afspejler et normaliseret niveau i selskabernes forretningscyklus.

Derfor udvikles der i dette speciale en række investeringsstrategier baseret på estimater af terminalværdien, der ved brug af historiske regnskabstal forsøger at undgå optimisme og bias. Vores værdiansættelser gør brug af Gordons vækst- og value driver formlerne, der anvendes i mange almindelige DCF-modeller. I specialet argumenteres der for flere forskellige måder at estimere de fundamentale komponenter i de to formler, hvorefter det testes, om disse variationer er robuste. Strategierne anvendes på de 727 ikke-finansielle aktier, der har været en del af S&P 500 indekset fra 2003 til 2018. Resultaterne sammenlignes med indeksafkastet, og det afkast, man ville have opnået, ved at følge anbefalingerne fra Morningstars uafhængige aktieanalytikere.

Ved at købe undervurderede aktier leverer strategierne i gennemsnit årlige afkast mellem 12,6 % og 17,6 % udover den risikofri rente, mens S&P 500 indekset uden finans har genereret 12,5 % årligt. En portefølje bestående af 4- og 5-stjernede aktier gav 13,1 % årligt men med en relativt høj risiko.

Gordon Growth og value driver strategierne er sammenlignelige i forhold til afkast og risiko, men det konkluderes, at de investerer i aktier med vidt forskellige karakteristika. Gordon Growth strategien investerer i aktier, der fremstår billige på multipler og har højere gæld, lavere marginer og lavere afkast på investeret kapital. Derimod investerer value driver strategien i billige aktier med højere kvalitet på disse parametre. Begge strategier favoriserer aktier i sektorerne for sundhed og stabilt forbrug, men de vurderer ofte, at teknologi-aktier er dyre. Hvis strategierne anvendes til både at købe billige aktier og sælge dyre, leverer de fortsat stærke risikojusterede afkast, men de er mindre konsistente, hvilket især gælder value driver strategierne.

Resultaterne er robuste på tværs af mange forskellige variationer af Gordon Growth og value driver strategierne, men hvis antagelserne om vækst og diskonteringsrente bliver for konservative, findes der færre billige aktier, hvilket gør strategierne mere koncentrerede og risikable. Diskonteringsrenten har desuden stor betydning for, hvilke sektorer der investeres i.

Resultaterne indikerer, at vores strategier udgør et bedre alternativ til den traditionelle kvantitative value faktor udviklet af Fama & French, der vurderer aktier på deres kurs/indre værdi. Value faktoren har klaret sig ringe i det sidste årti og er blevet overflødiggjort af nyere faktorer for rentabilitet og investering.

Table of Contents

1 – Introduction

Short term sentiment in irrational markets can lead to stock prices that deviate significantly from fundamental values (DeLong et al., 1989). This creates an opportunity for long term value investing to outperform.

To determine a company's intrinsic value, equity analysts spend much of their time forecasting financials several years into the future - although the explicit forecast period represents a limited share of total valuation (Platt, Demirkan & Platt, 2009, p. 19). Instead, most of the company's value is determined in the terminal period - a perpetuity including all of the years after the explicit forecast. Simultaneously, research indicates that the explicit forecast period is biased towards optimism and acts as a runway for extrapolating recent improvements in key ratios such as operating margins and returns on invested capital (Levine et al., 1998, Cowen, Groysberg & Healy, 2006). Instead, McKinsey (2015, p. 250) underlines the importance of normalizing economic profits to a mid-cycle level before the transition to the terminal value calculation.

To accommodate this, our thesis presents a single-period valuation model based on realized historical measures - thus eliminating the need for an explicit forecast period and related biases. The purpose is to estimate the value of stocks solely with a terminal value perpetuity and compare it to the prevailing market prices. The result is a price/fair value estimate meant to capture value opportunities in the market and generate superior returns (alpha). To study whether the single-period model is superior to analysts' cash flow models with an explicit forecast period, we will compare it to Morningstar's valuations of the S&P 500 companies and see which generates the highest risk-adjusted returns relative to the index in a 15-year backtesting.

Several quantitative factors of value already exist such as price-to-earnings and enterprise value-to-EBITDA, but the best-known work on a value factor was carried out by Eugene Fama and Kenneth French in 1992, which concluded that a low price-to-book ratio was the most predictive definition of value. However, some studies indicate that value factors have underperformed ever since the 2008 financial crisis (Northern Trust, 2018, Pedersen, 2015, p. 138), leaving value investors in need of new and more sophisticated tools to extract a value premium. To test the validity of the single-period valuation model, we will study its predictability of stock returns in the cross section and adjust its performance for several common risk factors.

1.1 Thesis Statement and Research Questions

The objectives outlined in the introduction results in the following thesis problem statement:

How does a quantitative terminal value model perform compared to Morningstar's equity recommendations and the S&P 500 over a 15-year period?

- What are the different practices for estimating steady-state free cash flows, operating profits and returns on invested capital?
- How does a terminal value model based on Gordon Growth compare to a model based on McKinsey's value driver formula?
- How are the valuations and performance of the terminal value models impacted by stressing critical variables such as WACC or growth?

The rest of the thesis is organized as follows. The remaining part of **Section 1** presents and evaluates the data sample and the applied Scientific Method. **Section 2** provides a theoretical framework of quantitative investing, equity valuations, Morningstar's equity research methodology, and how to perform a backtest. **Section 3** explains how the quantitative valuations are built, how we test Morningstar's performance, and which measures we use to evaluate risk and returns. **Section 4** provides a deep analysis of the investment performance of all the quantitative valuations and Morningstar's recommendations. **Section 5** discusses the results from the analysis and the construction of the models. **Section 6** presents the conclusions.

1.2 Data Sample, Sources of Error, and Delimitations

We gather data on stock prices, returns, accounting information, and Morningstar's equity ratings from Morningstar Direct. This section describes the sample and explains our treatment of data and the various biases and sources of error that may affect our results.

Universe and data sampling

We will focus our efforts on some of the most traded and covered equities in the world; the constituents of the S&P 500 index, which are considered one of the leading stock market indexes in the U.S. (McKinsey, 2015, p. 85). We suspect these stocks to be more efficiently priced and thus, generating abnormal risk-adjusted returns (alpha) in this environment should prove challenging. At the same time, the S&P 500 has performed exceptionally well compared to the MSCI All Country World Index over the past decades. The outperformance provides the valuation models in this thesis with an advantage, since they will only be stock-picking within some of the market's strongest performers. Throughout the analysis we have tried to adjust for this difference. Other studies such as Quality Minus Junk (2013) by Pedersen, Asness, and Frazzini include data from 24 developed markets. Naturally, our study is smaller which allows a deeper analysis.

The 15-year backtest stretches from the beginning of April 2003 to the end of September 2018 to illustrate whether the investment strategies have worked in a modern economic environment and through periods of turmoil such as the financial crisis of 2007-2008. Other studies of quantitative strategies include far more years than 15 - for example Quality Minus Junk (2013) by Pedersen, Asness, and Frazzini who include data from 1956-2012. The sample period has been limited to both improve data quality and emphasize the recent performance of the investment strategies presented in this thesis. In addition, Morningstar's coverage of the S&P 500 stocks was limited before 2003.

The data sample consists of 727 stocks constituting the S&P 500 index between March 2003 and September 2018. Financial firms such as banks and insurance companies have been excluded since they do not operate with the fundamentals we apply in our models (i.e. EBIT and operating assets). This is a similar practice to other studies such as Grey & Vogel (2012, p. 8) and Fama & French (1992, p. 429). Excluding financials results in stronger performance - especially during the financial crisis – and may give our portfolios an edge in comparison to the total stock market or the traditional S&P 500 index. The index includes both A and C shares for several stocks such as Alphabet, and we have excluded the least liquid stocks to avoid evaluating and investing in the same firm twice.

Accounting data and total returns have been collected in Morningstar Direct since 1992 because some of our variables are ten-year averages. The first available data in our regression and backtest is the 31st of March 2003. All accounting data, market cap and returns are in USD. Returns include dividends that are not reinvested but instead treated as a cash payout as of the end of each return period. In the event of a bankruptcy, delisting, merger or acquisition Morningstar computes the return until the last available trading price. We do not exclude firms due to these events, as this can bias results. We have not adjusted past accounting data for acquisitions, spin-offs and mergers. For example, eBay spun off PayPal in 2015 but our valuation of eBay in 2015 apply historical accounting data that includes the financials from both PayPal and eBay before the spin-off. After the spin-off, the financial results from eBay does not include the PayPal business, but because some of our valuation models apply up to 10-year historical results, these will mistakenly include results from both businesses when evaluating eBay on a standalone basis after 2015.

Monthly return estimates for the risk-free rate (Rf) and factors such as market (MKT), size (SMB), value (HML), and momentum (MOM) are obtained from Kenneth French's data library (mba.tuck.dartmouth.edu/ pages/faculty/ken.french). The risk factor data is based on all stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and Nasdaq. The risk-free rate is the return of a 1-month U.S. Treasury Bill (Fama & French, 1993, p. 7).

Lagging company fundamentals

In accordance with the SEC's deadline for Large Accelerated Filers (U.S. Securities and Exchange Commission, 2019), we assume that all annual reports (10-K) of the previous fiscal year (*t - 1*) have been published by the end of February which implies at least a 2-month lag (or delay) of the fundamentals we apply. For example, at the end of January 2018, the valuation models will still estimate fair values based on the data from the annual reports of 2016. This assumption is less conservative and timelier than the lag applied by Fama & French (1996, p. 61), in which both fundamentals and market caps are lagged 6 months. We do not lag market cap or stock prices, so our models compare valuations to the closing price on the last day of each month and executes the trade at the closing price same day. If we would use 6 months old market values or stock prices to evaluate which stocks to buy today, the stock prices could easily have risen to expensive levels today.

For firms with non-standard fiscal years such as Microsoft (fiscal Q4 is April, May, and June), the fundamental data of the annual report will be available much earlier than our model assumes. These firms are treated equally to firms with standard fiscal years, so the accounting data will not be made available for the valuation models before the end of February in the subsequent year. In practice, the models will utilize stale and outdated fundamentals in periods between the annual reporting cycles. One of the implications would be if a firm has grown its cash flow or operating profit significantly in a newly released quarter, then the market will have more than enough time to react on the new information, while our model will still only apply fundamentals from previous annual reports. One way to accommodate this challenge would be to use trailing four quarters data (TFQ) from Compustat (Nissim, 2017, p. 7), but this would require a much larger amount of data and complicate the process. TFQ data is not typically present in any of the companies' financial reports and this, in addition, would make it difficult to validate the fundamentals. The valuation models will at no point in time apply accounting information that has not already been released to the public markets at least two months earlier.

Look-ahead bias, data mining and other sources of errors

The monthly constituents of the S&P 500 have been collected from Morningstar Direct, and the quantitative models will only value the companies that are present in the index at the time of the valuation. This way, the models will not inherit a look-ahead bias of valuing and investing in companies that were previously not in the S&P 500 but moved into the index after our investment. For example, Amazon first went public in 1997 but did not join the S&P 500 index before November 2005. During this period, Amazon enjoyed a stellar cumulative return of 2.000% and its market capitalization grew large enough to be adopted in the index. If the quantitative valuation models would only consider the winners that grow large enough to be included in the S&P 500, they would indeed have an unfair advantage.

To limit the effect of data mining and increase robustness, we apply both Gordon's constant growth and McKinsey's value driver formula in our single-period valuation models and illustrate consistent results across a broad set of input measures (Asness, Frazzini & Pedersen, 2013, p. 9). If our results are robust across the many variations of our valuation models, it should be hard to argue that they stem from data mining.

The study does not measure the performance of consensus target prices or other recommendations than those from Morningstar. This is because one of the authors is employed at Morningstar, and we have previously studied the equity research and forecasts of Morningstar's analysts, providing us with valuable insights into Morningstar's valuation process. Using Morningstar's research as a representation of qualitative valuations limits our ability to make conclusions about the performance of equity analyst recommendations in general. Yet, studying data of Morningstar's valuations and recommendations directly from their own Morningstar Direct platform increases data quality.

Since this paper compares the performance of Morningstar's ratings for stocks and our quantitative valuations of the S&P 500 index excluding financials, it's relevant to point out that Morningstar does not always cover every constituent of the index at any given time. Stocks can also be placed "under revision" in rare cases by Morningstar - for example if a company experiences periods of large uncertainty. When a stock is under revision, it has no star rating or fair value. In the beginning of our sample period, Morningstar covers only 56% of our valuation models' investable universe, although this share increases gradually to 84% in August 2004 and then increases further towards 89% at the end of the sample period with only minor fluctuations. This implies that some of the differences in performance between the quantitative models and Morningstar's recommendations could stem from the two not being able to invest in exactly the same stocks - especially in the first 1.5 years of the backtest. For these reasons, it will be a central part of the thesis to also benchmark Morningstar's performance against the market and not only compare it to our quantitative models.

Additionally, our quantitative valuation models may estimate a negative fair value if historical fundamentals such as EBIT or FCFF have been negative. The backtest of the quantitative trading strategies ignores such negative valuations and excludes them when grouping the performance into deciles. This means, that even though the S&P 500 excluding financials and duplicates typically contain around 430 stocks, an average of 20 firms in our sample have negative EBIT in any given year. Those of the quantitative models based on last year's EBIT will neither take long or short positions if this is the case.

An alternative method, which we do not apply, is Winsorizing, where the negative price/fair value estimates are set equal to our samples highest (most overvalued) P/FV. Since negative cash flows and operating income could be characteristics of distressed companies, this method would put distressed stocks in the most overvalued percentile of our sample. This implies that all these firms are vastly overvalued based solely on their negative FCFF and EBIT while ignoring their market value. This would be an aggressive and perhaps even misguided assumption, as some of these firms could be bargains, since distressed companies are usually cheap with a low price compared to book value (a common value factor presented by Fama & French, 1993). If we Winsorized our results, our P/FV decile-based long/short portfolios would short sell the stocks with negative fair values, and we do not want this to influence our results.

Morningstar, on the other hand, continuously deliver valuations and recommendations on the companies in their coverage universe, and loss-making companies are not excluded when we evaluate risk and return of Morningstar's ratings. This could be a source of difference when comparing Morningstar's performance with the terminal value models.

Several of our quantitative models apply 3-, 5- or 10-year average fundamentals, but if a firm does not have 5 years of accounting history, our 10- and 5-year models will not compute any valuation. If there is data missing for any one or more years, the valuation models based on the fundamentals in these years will not make a valuation. The magnitude of this implication is that on our first valuation in 2003, we do not have financials from 1992 for 71 out of 409 S&P 500 constituents. Each year from 2003 to 2018, our 10-year based models do not have 10-year fundamentals from between 60 to 86 constituents. The valuation models based on last year fundamentals are only missing data for around 15 firms on average. Thus, the investment portfolios based on the 10-year valuations will have fewer companies to pick from and can end up being less diversified and more volatile as a consequence, which may reduce the statistical significance of the results. The upside is that our 10-year models will not estimate a fair value identical to that of the 3-year model, just because the company only has 3 years of accounting history. Additionally, this makes it difficult to perform valuations based on fundamentals across a whole business cycle, as a decent number of firms (in our sample) simply do not have such long public accounting history.

Since our data sample, the S&P 500, is heavily biased towards highly liquid and large cap stocks, it also inherits an implication considering the well-known size effect (Alquist, Israel & Moskowitz, 2018) and may eliminate any liquidity premiums.

No matter how we slice the cake, our portfolios will not get exposure towards small or micro-cap stocks. Fama & French (1993) might argue that this bias should result in lower, average returns, while others find that the largest stocks have outperformed over time (Rekenthaler, 2018) or that the size effect have disappeared since its discovery (Alquist, Israel & Moskowitz, 2018, p. 8). Research from the latter indicate that factor strategies such as value and quality are more consistent and work better within small stocks - thereby indicating that by not including small stocks in our sample, we run the risk of seeing smaller and less significant outperformance from the terminal value-based strategies. Since our sample does not include both small and large firms, we will not take a deep dive into how size affects the performance of the quantitative valuation models.

1.3 The Scientific Method

The research in this thesis has a deductive angle, because the trading strategies are designed based on a theory and not based on what has performed best historically. This is important for these types of research papers, since the latter would be datamining, which undermining the results. It is easy to find something that has historically outperformed with the benefit of hindsight bias. It proves to be much harder to find a sensible strategy that has performed historically (Andersen, 2013, p. 31 and p. 265).

The thesis has a positivistic approach as it depends on quantitative data with a deep focus on accounting and market data. Since there are various ways to measure the performance of a strategy, the ontology can be discussed, but in general it is a positivistic study (Guba, 1990, p. 19-27, and Heldbjerg, 1997, p. 30).

The positivistic interpretation (realistic ontology) of portfolio theory would be that the optimal portfolio is dependent on the laws of the markets (that the market is efficient). But this thesis actually tries to identify an anomaly by designing a unique strategy that can outperform the market, so we could argue that the research has a slight constructivist angle. Therefore, we characterize the thesis as neo-positivistic, since it is partly arguing against an efficient market but follows standard performance measures of whether the strategy works or not.

The data is collected in an objective way. Even though we recognize that complete objectivity is not possible. This can also be observed in the quantitative data, which the thesis is driven by, even though some manipulation has been performed in the form of excluding financial companies and duplicates. This is all in line with a neo-positivistic approach, which is an objective and structured approach with high validity and reliability (Saunders, Lewis & Thornhill, 2012).

To ensure that our findings are trustworthy and credible, we need to optimize the validity and reliability of the research. Internal validity refers to the cause and effect relationship, while external validity refers to whether the results can be used in other contexts, which is crucial for this assignment, since the strategies should be reliable for practical use. Reliability means the data can be trusted and that another researcher would achieve the same result if the analysis was repeated (Andersen, 2013, p. 270-275).

The internal validity of the thesis is high, since a backtest has been performed with historical data, so the results can be replicated. The uncertainty comes when we discuss the external validity, since it is not certain whether the strategies will work in other circumstances or in the future. The internal validity of the research is high, as all data is publicly available, both accounting and market data. It is also high, since we have limited the research to a recent period from 2003 to 2018 and S&P 500, where the data is more robust and of higher quality. As such, we have had the opportunity of double-checking much of our data to ensure that it is correct. The research we rely on for estimating the different inputs in the valuation models is all reliable well-known research papers, which increase the validity of the thesis (Andersen, 2013, p. 270-275).

The reliability of the research decreases somewhat, since the conclusions depend on historical data and is limited to a narrower sample of S&P 500 stocks in a relatively short time period. However, the short time period can also be positive for the reliability, because it is not necessarily relevant how stocks behaved 50 years ago (Andersen, 2013, p. 270-275).

2 – Theoretical Framework

2.1 Quantitative Equity Investing - Literature Review

The objective of our quantitative terminal value models is to find undervalued stocks that will produce superior future returns based on the companies' past ability to generate free cash flows. This fits into an old tradition of investment managers attempting to create superior strategies to beat the market. For this reason, we will begin the section with a quote from one of the leading characters in quantitative equity investing:

"I think that good quant investment managers ... can really be thought of as financial economists who have coded their beliefs into a repeatable process. They are distinguished by diversification, sticking to their process with discipline, and the ability to engineer portfolio characteristics"

- Cliff Asness (2007)

In quantitative investment management, the strategy is model-driven and consistent. Quantitative investing is a contrast to discretionary investment management, because the investments are the result of a quantitative model and not based on the investment manager's judgment.

There are several advantages and disadvantages to quantitative strategies. Firstly, the trading rules are not very flexible and cannot be adjusted to specific situations. Secondly, they typically do not consider soft information such as phone calls or human judgement - this type of information is more suitable for discretionary investing. The advantages are, that the strategies can be applied to a broad set of stocks and instantly evaluate all of them, and the manager does not need to evaluate each company individually. Secondly, quantitative models avoid human behavioral biases as they are simply algorithms making investment decisions based on certain rules. Another advantage is that quantitative models can be backtested with historical data, making it possible to measure how it would have worked in the past. This is possible because the data quality of returns and company financials is very precise (Pedersen, 2015 p. 133-134).

According to Pedersen (2015), three types of quantitative equity investing exists. These are Fundamental quantitative investing, statistical arbitrage, and high-frequency trading (**Appendix 1**). The models presented in this thesis are based on company fundamentals. Fundamental quantitative investors base their trades on factors such as value, momentum, quality, size or risk. The underlying building block is the same across these factors - they provide quantitative estimates of which stocks that have high or low expected returns (Pedersen, 2015 p. 135). Pedersen (2015, p. 136-144) presents 4 different types of fundamental quantitative investing that we have summarized in **Table 2.1** below.

Table 2.1: Overview of quantitative investment strategies

	Value investing	Stock momentum	Quality investing	Low risk investing
Strategy	Long cheap stocks, short expensive stocks	Long high performing stocks, short low performing stocks	Long high quality, short low quality	Long low risk, short high risk
Common measures	Book to market Earnings to price Dividends to price Cash flows to price	Last 12-month, minus 1-month average return	Profitability, earnings quality, sustainable growth, safety, payout and management quality	Beta
Common factor	High minus low (HML) (Fama & French, 1992)	Up minus down (UMD) (Asness, 1994)	Quality minus Junk (QMJ) (Assnes, Frazzini, Pedersen, 2015)	Betting against Beta (BAB) (Pedersen & Frazzini, 2013)

Overview of quantitative investment strategies

Source: Efficiently Inefficient (Pedersen, 2015) and own production.

Quantitative value investing is about systematically calculating a measure of a stock's fundamental value and then compare it to the current market price. The strategy is to buy the companies with high fundamental value compared to current market price and sell the opposite. Value investing can work for any variable that can reasonably be used to reflect the relative market price to some fundamental value. The most known value strategy is to buy the 30% of stocks with highest book to market and short the 30% with lowest book to market. This is also one of the factors in the 3-factor model together with size (Fama and French, 1993).

Stock momentum is a strategy that buys stocks which have recently outperformed in terms of returns and shorts those which underperformed. A common implementation is to evaluate the performance over the most recent year, leaving out the single most recent month. Then go long the stocks with the highest average returns in this period and short the opposite. Momentum has strong historical performance, beating that of value - especially since 1997 (Pedersen, 2015, p. 138). An interesting fact about value and momentum is that they are usually negatively correlated, which makes a mix of these very strong. A value stock with positive momentum is a cheap stock on the rise, and these have performed very well historically across markets (Asness, Moskowitz & Pedersen, 2013, p. 953).

Quality investing is a natural complement to value investing. This strategy buys high-quality and shorts low-quality stocks. Quality can be measured from many different variables such as; profitability, growth, stability, and management. Isolated, quality does not consider the price, as a high price is assumed to be justified by high quality. According to Assnes, Frazzini & Pedersen (2013) in their paper "Quality Minus Junk", this strategy has delivered positive abnormal returns on average for both U.S. and global stocks. Just as momentum, it is a very strong combination with value, and even stronger when combined with both value and momentum according to Pedersen (2015, p. 140).

Low risk investing is basically buying stocks that have a low correlation to the market (expressed as beta) and short selling stocks that are more sensitive to the general stock market. According to Pedersen & Frazzini (2013), many investors such as pension funds have constraints to how much leverage they can apply, so they overweight risky securities instead of leveraging securities with lower risk. This tilt towards high-beta assets suggests that risky assets provide lower risk-adjusted returns than low-beta assets. This strategy has on average been generating a Sharpe ratio of 0.78 (Pedersen, 2015, p. 141).

Naturally, the strategies presented in this paper are closest to quant value investing, since the valuations are based on company fundamentals. The most common value investing strategies are applied on the basis of simple multiples in contrast to our strategies, which are actual valuations based on cash flows, operating profit, growth, cost of capital, and the value of net interest bearing debt. In this way, our estimates are closer to those calculated in a regular discounted cash flow (DCF) model applied in many discretionary equity valuations.

2.2 Equity Valuation

To understand how to construct a quantitative valuation model, one must first grasp the principles of estimating the intrinsic value of a company. That is the objective of this section.
The most common approaches of estimating the value of a company are the following:

- Present value models
- Multiples
- Sum-of-the-parts
- Contingent claim valuation

The ones most frequently used in practice are the present value and multiple based models (Plenborg, Petersen & Kinserdal, 2017, p. 299).

The aim of a good valuation model is to have the following qualities; 1) precision, 2) realistic assumptions, 3) user friendly, 4) understandable output. A precise valuation must approach an unbiased estimate and be theoretically consistent. Any assumptions should be realistic with respect to the firm’s past performance. A user friendly and understandable model should have a low level of complexity, be easy to access, time efficient to use, and can be communicated in layman’s terms (Plenborg, Petersen & Kinserdal, 2017, p. 299-300). The aim of this thesis is to construct a model that has all these qualities. The present value method will be outlined below, as this is the base of our quantitative models.

The present value model estimates the value of a company by discounting the analyst’s future projections of cash flows or dividends, because a dollar earned today is worth more than a dollar earned tomorrow. The discount rate depends on how risky the company is. All present value approaches are derived from the dividend discount model. But since dividends are not the best measure of a company’s ability to generate cash flows, it is not widely applied in practice, but all other present value models have the equivalent theoretical framework.

The most popular model for valuation in practice is the discounted cash flow (DCF) model (Plenborg, Petersen & Kinserdal, 2017, p. 299). In contract to the discounted dividend model, a DCF discounts free cash flows. The free cash flow is a good proxy of amount that theoretically could be paid out to shareholders, if the company had no debt. The future cash flows are discounted by the weighted average cost of capital (WACC) which consists of the required return on debt (weighted by the amount of interest bearing debt) and the required return on equity (weighted by the equity on the company's balance sheet).

$$Enterprise\ Value_0 = \sum_{t=1}^{\infty} \frac{FCFF_t}{(1 + WACC)^t}$$

$$FCFF_t = Operating\ Cash\ Flow_t + Investing\ Cash\ Flow_t$$

FCFF: Free cash flow to firm
t: Current time period
WACC: Weighted average cost of capital (used as a discount rate for future cash flows)

According to the formula above, the total value of an enterprise is the sum of all discounted free cash flows that the company can produce in the future. Practically, it is not possible to explicitly forecast cash flows each year until the end of times, so after an explicit forecast period, the analyst assumes the company to reach a so-called "steady-state level", where free cash flows grow with the same rate each year in perpetuity.

$$Enterprise\ Value_0 = \frac{FCFF_t}{(1 + WACC)^t} + \frac{FCFF_{n+1}}{WACC - g} \times \frac{1}{(1 + WACC)^n}$$

g: The long-term stable growth rate (in the terminal value period).
n: Number of periods with non-constant growth rates (forecast horizon).

The basic idea behind the two-stage model is that the growth of a company will eventually reach the long-term growth rate of the economy in which the company operates. Since all companies are not at the same stage of their life cycle, the forecast horizon deviates between companies.

The assumption that growth remains constant in steady-state may seem unrealistic, but it is a pragmatic solution to a time-consuming task of forecasting all cash flows explicitly. The value of the cash flows after steady-state can be identified as the “continuing value” or “terminal value”. It is often calculated with the Gordon Growth model (Myron J. Gordon, 1962):

$$v_0 = \frac{D_0 \times (1 + g)}{r - g}$$

v_0: Present value
D_0: Dividend in period 0 (today)
r: Required return

Basically, the Gordon Growth formula is just calculating the present value of an infinite stream, or perpetuity, of cash flows. In a DCF valuation, the formula is usually written as follows:

$$Terminal\,Value = \frac{FCFF_0 \times (1 + g)}{WACC - g}$$

The (1+g) is applied because the company should be evaluated on what free cash flow it can generate in the next period and not what it has generated in this period. It is essential that a company is not worth its historical cash flows but its future cash flows - although, ironically, this is the assumption that our quantitative terminal value models will violate as described in **Section 3**. Historical cash flows can be useful when estimating future performance or to determine whether the forecast assumptions are realistic (Plenborg, Petersen & Kinserdal, 2017, p. 302).

Companies that reinvest a substantial portion of their cash and earn high returns on these investments should be able to grow at high rates, but it is difficult to tell for how long. When a company grows larger, it becomes more difficult to maintain the growth, and eventually it will grow at a rate less than or equal to the economy it operates in. When estimating growth in the terminal period, the analyst needs to consider the firm’s size relative to the market it serves, its current growth, and its competitive advantages (Damodaran, 2002, p. 425).
When determining steady-state growth, the analyst should also consider whether a company is operating as a domestic or international company, and whether the valuation is carried out in nominal or real terms. If the valuation is nominal, the stable growth should also be nominal vice versa. As an example, Coca Cola’s stable growth can be as high as 5.5% in nominal USD but only 3% in real USD due to inflation. The last consideration is the currency being used to estimate cash flows, because the growth will vary depending on whether it is a high- or low-inflation currency. If a high-inflation currency is used to estimate cash flows the limits of stable growth will be much higher since the expected inflation rate is added to the real growth (Damodaran, 2002, p. 429).

Since not all companies have no debt, and because the value of a company should be calculated on a debt free basis, the value of net interest bearing debt (NIBD) is calculated as follows:

$$NIBD_t = Financial\ Liabilities_t - \ Financial\ Assets_t$$

NIBD is simply all the company's interest bearing debt minus any cash, securities or liquid funds that could be used to pay off the debt. The financial assets and liabilities can be determined in different ways but are usually determined by evaluating the balance sheet and categorizing both assets and liabilities as either operational or financial. This is primarily determined by what is interest bearing and what is not (Plenborg, Petersen & Kinserdal, 2017, p. 114).

When NIBD is deducted from enterprise value, the equity value is determined as follows:

$$Equity\ Value_t = \frac{FCFF_t \times (1+g)}{WACC - g} - NIBD_t$$

It is essential in the terminal period that the free cash flow has reached a steady-state level, since the value in the terminal period (as opposed to the explicit forecast period) accounts for the majority of the total value of a company. In some cases, the terminal value accounts for 97.5% of the total value (Platt, Demirkan & Platt, 2009, p. 19). If the free cash flow is overstated in the calculation, then the value will be overstated as well. This makes it crucial to perform a forecast review to evaluate how realistic the estimate is. The suggested numbers to look at is growth, EBITDA-margin, and return on invested capital (Plenborg, Petersen & Kinserdal, 2017, p. 279). According to McKinsey, it is just as important that the estimates at the end of the explicit forecast period represent a normalized mid-cycle level of the business (McKinsey, 2015, p. 250).

The discounted cash flow model rests on the assumption that all excess cash is paid out either as dividends or reinvested in projects with a net present value of 0 (Plenborg, Petersen & Kinserdal, 2017, p. 307).

The relationship between multiples and present value

This section demonstrates the relation between multiples and present value approaches. Below we will derive Enterprise Value (EV) based multiples from the DCF model.

We know that enterprise value with a constant growth rate and a steady-state free cash flow is calculated as the following:

$$Enterprise\ value_t = \frac{FCFF_{t+1}}{WACC - g}$$

If we replace FCFF with net operating profit after tax (NOPAT) we get the following:

$$Enterprise\ value_t = \frac{NOPAT \times (1 - reinvestment\ rate)}{WACC - g}$$

$$Reinvestment\ rate = \frac{\Delta Net\ working\ capital + \Delta Non-current\ operating\ assets}{NOPAT}$$

The reinvestment rate describes how much of the operating profit that must be reinvested in the business. If we substitute NOPAT with ROIC times invested capital and divide by invested capital on both sides, we get an enterprise value/invested capital multiple:

$$\frac{Enterprise\ value}{Invested\ capital} = (\frac{ROIC \times Inv.capital \times (1 - reinvestment\ rate)}{WACC - g})/Invested\ capital$$

$$(=)\frac{Enterprise\ value}{Inv.capital} = \frac{ROIC \times (1 - reinvestment\ rate)}{WACC - g}$$

$$(=)\frac{Enterprise\ value}{Inv.capital} = \frac{ROIC - g}{WACC - g}$$

The reason why growth is equal to ROIC times the reinvestment rate as shown above, is because the return on what is invested in the business is how much the business is growing.
If we then multiply the expression by 1/ROIC on both sides of the equation we get Enterprise value/NOPAT:

$$\frac{Enterprise\ value}{NOPAT} = \frac{ROIC - g}{WACC - g} \times \frac{1}{ROIC}$$

If we then multiply both sides of the equation by 1-tax we get enterprise value/EBIT, and substitute NOPAT by EBIT×(1-t):

$$\frac{Enterprise\ value}{EBIT \times (1 - t)} \times (1 - t) = \frac{ROIC - g}{WACC - g} \times \frac{1}{ROIC} \times (1 - t)$$

$$\frac{Enterprise\ value}{EBIT} = \frac{ROIC - g}{WACC - g} \times \frac{1}{ROIC} \times (1 - t)$$

To get enterprise value/EBITDA which practically has become a very popular multiple, we multiply both sides of the equation by 1- the depreciation rate (DR) and substitute EBIT with EBITDA×(1-DR).

$$\frac{Enterprise\ value}{EBITDA \times (1 - DR)} \times (1 - DR) = \frac{ROIC - g}{WACC - g} \times \frac{1}{ROIC} \times (1 - t) \times (1 - DR)$$

$$\frac{Enterprise\ value}{EBITDA} = \frac{ROIC - g}{WACC - g} \times \frac{1}{ROIC} \times (1 - t) \times (1 - DR)$$

Ultimately, the algebra above simply proves that the present value of a firm can explain the very popular multiples that are often utilized without much thought given to the underlying mechanics. As we see above, an attractive enterprise multiple might be explained by low growth expectations, high risk (WACC), low returns on invested capital or a high reinvestment rate (Plenborg, Petersen & Kinserdal, 2017, p. 319-320).

When evaluating companies based on multiples, it is important that the companies are comparable. It is often assumed that companies can easily be compared if they are within the same industry, but in fact, they also need to be comparable in terms of accounting standards, growth rates, cost of capital, profitability, tax rates and depreciation practices.
The tax rate and accounting standard can be hard to adjust if the peers are operating in different countries. In terms of the depreciation rates the way companies depreciate and amortize their assets also needs to be equivalent. It can also be challenging if one company in-source its production while a peer has outsourced, which will impact the depreciation rate (Plenborg, Petersen & Kinserdal, 2017, p. 322).

One of the most frequently used multiples, which we also derived above, is enterprise value/EBITDA. This multiple also needs to be adjusted for accounting standards, WACC, growth, tax rate, and depreciation rate (Plenborg, Petersen & Kinserdal, 2017, p. 322), if any of the peers have a different practice. It can be very tempting to quickly evaluate companies with multiples, but to adjust all parameters correctly is a big task.

2.3 Morningstar's Equity Research Methodology

Morningstar analysts estimate the value of equities with a proprietary discounted cash flow model. The Morningstar rating for stocks identifies stocks trading at a discount or premium to their fair value estimate and ranks these from one 1 to 5 stars. 5-star stocks trade at the largest risk-adjusted discount to their fair values, while 1-star stocks sell at premiums to their fair value (Morningstar Equity Research Methodology, 2015).

The star rating is driven by four key components which we will explain in this section:

- Morningstar's assessment of the company's sustainable competitive advantages (economic moat)
- The estimate of the firm's fair value
- The uncertainty related to that fair value estimate
- The current market price of the stock.

The valuation model is divided into three stages; an explicit forecast period, a maturing phase (Fade) and a terminal value perpetuity.

Stage 1: Explicit Forecast

In the explicit forecast period (Stage 1), the analyst creates detailed estimates five to ten years into the future for the firm's financial value drivers to estimate earnings before interest, after taxes (EBI) and net new investments (NNI) to derive the free cash flow forecast.

Stage 2: Fade

The second stage is the period it will take for the company's return on new invested capital - the return of the next dollar invested (RONIC) - to decline (or rise) to its cost of capital. In Stage 2, Morningstar applies a formula to approximate cash flows instead of explicitly forecasting the income statement, balance sheet, and cash flow statement as in Stage 1. The length of the second stage depends on the strength of the company's competitive advantages (economic moat). This period can last from one year for companies with no moat to 10–15 years or more for wide-moat companies.

Cash flows and Stage 2 value are calculated with a finite perpetuity formula with four inputs;

1) A constant growth (g) in EBI over the period
2) A normalized investment rate (expressing the share of earnings to be reinvested)
3) Average return on new invested capital (RONIC)
4) The number of years (L) until Stage 3, when excess returns cease.

$$Stage\ 2\ value = \frac{EBI_{(T+1)} \times (1 - IR)}{WACC - g} - \frac{EBI_{(T+L+1)} \times (1 - IR)}{(WACC - g) \times (1 + WACC)^{L}}$$

$$Stage\ 3\ value = \frac{EBI_{(T+L+1)}}{WACC}$$

T: Length of stage 1

IR: Investment rate = G/RONIC

(Morningstar's DCF valuation models, 2018)

Stage 3: Perpetuity

The terminal period or continuing value includes every year after Stage 2 and is calculated as a perpetuity based on McKinsey's value driver formula (McKinsey, 2015, p. 31). In stage 3, the return on new invested capital (RONIC) is set equal to the cost of capital (WACC). The underlying assumption is that any growth or investment neither creates nor destroys value after this point (McKinsey, 2015, p. 22).

All cash flows in Stage 1, 2, and 3 are discounted to derive a total present value of all expected future cash flows - or rather, the enterprise value. Since the free cash flows to the firm (FCFF) represent the cash available for both owners and lenders, the discount rate used is WACC, which is the average cost of equity, debt and other funding sources weighted by the market value of these.

Uncertainty around the fair value estimate

Morningstar's uncertainty rating helps determine the margin of safety required for awarding a particular star rating to a company. The more uncertain the analyst is about the estimated value of the equity, the greater the discount required relative to the fair value estimate. The uncertainty describes the accuracy of the fair value estimate. The lower the uncertainty, the narrower potential range of outcomes for the particular company based on the characteristics of the underlying business including operating and financial leverage, sales sensitivity to the overall economy, product concentration, pricing power and other company-specific factors (Morningstar, 2015, p. 8).

The uncertainty ratings are divided into low, medium, high, very high and extreme. Each uncertainty rating has a corresponding set of price/fair value ratios that the star ratings depend on as shown in **Appendix 2**. For example, a stock with low uncertainty will be awarded a 5-star rating if it is trading with a discount of 25% or more to the fair value and will only receive 1 star if the share price is 25% higher than the estimated fair value. In their uncertainty rating, Morningstar accounts for operating and financial leverage, the predictability of sales, and the risk of a future event - such as product approval or legal decisions - impacting their valuation (Morningstar, 2015). Morningstar analysts also consider a bull- and bear-scenario in which the outcome of the company's fundamentals differ from their base case.

Morningstar star rating for stocks

The analyst's fair value of a stock is compared to the current market price and the star rating is recalculated every day the market, which the stock is listed on, is open. There is no predefined distribution of stars, so the percentage of stocks with 5 stars can fluctuate daily, and in times when valuations are high, there might be a shortage of 5-star opportunities. Morningstar expects the market price to converge on the fair value estimate over time - generally within three years.

How Morningstar estimates WACC, invested capital, and net interest bearing debt

Since WACC, invested capital and net interest bearing debt are important components of the terminal value models presented in this thesis, we were curious to look at how Morningstar estimates these fundamentals. Morningstar computes Total Invested Capital as:

$$Total\ Invested\ Capital = Total\ Working\ Capital + Net\ PP\&E + Net\ Intangibles$$
$$+ Capitalized\ R\&D + Goodwill + Capitalized\ Operating\ Leases$$
$$+ Capitalized\ Other\ Expenses + Net\ Other\ Assets$$

This measure of invested capital is applied in Morningstar's calculation of ROIC as:

$$ROIC = \frac{EBI}{(Total\ Invested\ Capital_t + Total\_Invested\_Capital_{t-1})\ /2}$$

Where EBI = EBITA × (1 - tax rate).

In their estimates of invested capital and ROIC, the analysts decide whether goodwill is included. Whereas goodwill is always assumed to be an operating asset in our quantitative proxy of invested capital and when we estimate ROIC. An argument for excluding goodwill is to ignore the distortion from premiums paid for acquisitions (McKinsey, 2015, p. 105). The assumptions underlying the use of EBITA and EBI instead of EBIT and NOPAT are outlined in **Section 3**.

To arrive at the total equity value after having estimated enterprise value, Morningstar's analysts add Cash & Investments while subtracting Short-Term Debt, Long-Term Debt, Pension Liabilities and Preferred Stock. This calculation is similar to the approach used by our quantitative terminal value models, where we subtract Net Interest Bearing Debt (NIBD). A key difference is that our proxy for NIBD does not include pension liabilities but instead assumes them to be operating liabilities which we subtract from invested capital. In our opinion, employee pension liabilities are operating in nature just like any other employee compensation, but because some firms estimate these liabilities at discounted fair value, they can also be classified as financial liabilities (Sørensen, 2012, p. 178).

Morningstar determines WACC by estimating cost of equity (COE) and cost of debt. These are weighted with the share of equity and debt respectively to arrive at WACC. A firm's cost of equity represents the average return expected by shareholders, but since these expectations are not directly observable, they must be estimated. Morningstar's COE consists of 4 building blocks (Morningstar, 2017).

1. The base is the Market Average Real Return Expectation of 6.5%-7.0% based on the long-term real return of the S&P 500.
2. Inflation Expectations of 2%-2.5% based on stable 10- to 30-year inflation expectations derived from U.S. TIPS spreads and actual consumer price inflation over the last decade.
3. Country Risk Premium inspired by Aswath Damodaran of the Stern School of Business at New York University. There is no country risk premium for U.S. firms.
4. Systematic Risk Premium based on four risk categories from Below Average to Very High. The premium ranges from -1.5% to 4.5% based on the category.

Cost of debt is based on a risk-free rate of 4.5%, the same inflation expectations as above, and a corporate credit spread depending on the firm's credit risk. Cost of debt is adjusted for taxes (because interest payments are deductible). The pretax cost of debt may range from 5.25% to 14.50% depending on the firm's credit rating (Morningstar, 2017).

2.4 Backtesting and Transaction Costs

To backtest a trading strategy means to evaluate how it would have performed historically. This does not guarantee future performance, but it is nevertheless a good tool for predicting future performance and sort out good or bad trading strategies. A backtest can also provide indications of the risk level of a strategy and ideas on how to improve it (Pedersen, 2015 p. 47).

To perform a backtest we need the following inputs (Pedersen, 2015 p. 48):

- **Universe:** The securities which can be bought and sold
- **Signals:** The data which is analyzed to provide signals to buy and sell.
- **Trading rules:** The trading frequency, rebalancing and the weighting of the positions.
- **Time lags:** If a strategy should be implementable, the data, that it is based on, should have been available at the time of investment. If a strategy uses a closing price as a signal, it is not realistic to assume that you can trade on the same closing price - however, this is a simplified assumption often made by academics.

For all trading strategies and backtests, trading costs and biases need to be considered. Typically, backtests look better than they would when implemented in practice. This is first of all because the financial markets are changing, and trading strategies that used to work might not work going forward, because more investors might pursue previously profitable strategies resulting in competitive pressure that may adjust market prices and reduce profitability.

All backtests suffer from data mining biases. For example, when analyzing different versions of a trading strategy, the analyst will tend to gravitate towards the implementations that have performed better - even though it would have been impossible to know before the backtest, which implementations would work best. Due to such biases, practitioners should discount the results of backtests and put more weight on realized returns. Especially if the backtests have been tweaked and optimized extensively. There are also a couple of avoidable biases described below, that we will make certain to eliminate in this thesis (Pedersen, 2015 p. 49).

When backtesting in a universe of the current S&P 500 stocks included in the index today, then the backtest will be biased if it is not adjusted to only consider the historical constituents in the index at the time of investing. Stocks are often included in an index because they have performed well, and you cannot know which companies are included in an index before the fact. If the strategy invests based on accounting information, it is important to be aware of the time of reporting for the specific companies, as you cannot trade on financials that have not yet been reported at the time. The single most important part of a strategy is to find one that will perform well going forward and not necessarily have the best possible backtest. Robust performance will not change dramatically when adjusting the process marginally (Pedersen, 2015 p. 49).

Transaction costs

Implementation of a trading strategy can be costly due to two types of transaction costs; explicit and implicit. The explicit costs are the ones known before a trade occurs, and they can be clearly measured and accounted for. These are commissions, taxes, and fees. The implicit costs are harder to measure and are related to the impact of the transaction on the market prices during and after the execution of a trade. Examples of these are spread and slippage versus reference price (Hedayati, Hurst & Stamelos, 2018, p. 4-8). Transaction costs reduce the returns of a trading strategy, so a backtest is more realistic if it accounts for transaction costs. The higher the turnover, the more important it is to adjust for transaction costs (Pedersen, 2015 p. 50).

The S&P 500 (our universe) is a liquid market with small minimum tick sizes (the minimum price amount a security can move in an exchange), while the bid-ask spreads and commissions are small. The amount that can be traded within the bid-ask spread is often small relative to what large institutional investors would trade. Therefore, the main transaction costs are often the market impact. If the transaction size increases, the market impact will be larger, and the costs will be higher. A way to limit transaction costs is to split up the trade into small orders patiently over time (Pedersen, 2015 p. 61). Engle, Ferstenberg & Russell (2012) estimate average transaction costs of 8.8 basis points (bps) for NYSE stocks based on orders executed by Morgan Stanley in 2004. It is less for small orders; only about 4 bps. In a sample of US stocks from 1998 to 2011, Frazzini, Israel & Moskowitz (2012) found a median transaction cost of 4.9 bps. Transaction costs rise considerably when the trade exceeds 10% of the typical volume in a stock, so traders usually try to avoid this (Pedersen, 2015 p. 70).

3 - Valuation Models and Inputs

This section describes the methodology for constructing the single-period valuation models based on Gordon's constant-growth (Gordon, 1962) and McKinsey's value driver formula (McKinsey, 2015, p. 31) and provides academic justification for estimating the inputs. We finish the section by presenting our methodology for backtesting and evaluating the performance of our models.

3.1 Gordon Growth Terminal Value

As we quickly introduced in **Section 2.2**, the Gordon Growth formula is often applied in discounted cash flow models to estimate the terminal value as an infinite stream, or perpetuity, of cash flows:

$$Terminal\ Value = \frac{FCFF_0 \times (1+g)}{WACC - g}$$

The section below explains how we estimate the parameters in our Gordon Growth model.

Weighted average cost of capital (WACC)

The cost of capital used as a discount rate for future cash flows is estimated by weighting the cost of equity (r_e) with the company's total equity (E), and weighting the cost of debt (r_d) after tax with the company's total debt (D), as the following formula suggests (Plenborg, Petersen & Kinserdal, 2017, p. 341):

$$WACC = \frac{E}{D+E} \times r_e + \frac{D}{D+E} \times r_d * (1 - tax)$$

The cost of equity is usually estimated with the capital asset pricing model (CAPM) as a premium over the risk-free rate (r_f) that depends on the market risk (β) of the stock and the market risk premium (r_m), as follows:

$$r_e = r_f + \beta \times (r_m - r_f)$$

The cost of interest bearing debt consists of two components; the risk-free rate and the credit spread. The credit spread is equivalent to the risk premium on debt (Plenborg, Petersen & Kinserdal, 2017, p. 363).

There are different methods of estimating WACC. In this thesis, it is essential that WACC can be estimated quantitatively across 727 companies for 15 years and provides a reasonable estimate of the cost of capital in steady state. Penman (1998) suggests the following two methods. The first is to determine WACC each year with a 6 percent equity risk premium and a beta computed for every individual company, which is then updated each year. The risk-free rate is assumed to be the rate on 3-year U.S. treasury bills. The second method is to simply apply a fixed cost of capital of 10% for all firms in every year as a rough but much simpler estimate. Penman concluded there was little difference between the results of the two methods and reasonable risk adjustments could not explain the results (Penman, 1998).

In terms of applying the same WACC across periods, previous research indicates there is no major errors in using a constant discount rate if some simplifying assumptions are upheld; constant market parameters, validity of CAPM, and the ability to estimate beta for specific assets. These are the conditions of a standard capital asset pricing model (Myers & Turnbull, 1977).

Another approach is to only determine the cost of equity and apply the assumptions of Modigliani and Miller (1963) - that capital structure does not matter. This implies that WACC is the same for different capital structures. As a result, it would be unnecessary to consider the cost of debt. This can be done both on a company specific level and an industry level by creating portfolios of different industries and unlevering the betas (Kaplan & Ruback, 1995).

Yet another method would be to calculate WACC for all companies in the sample by assuming that their systematic risk (beta) is equal to the risk of the market (1), or rather, an unlevered asset beta of the market (Kaplan & Ruback 1995, p. 9).

Since our data sample is the S&P 500 index constituents, which are some of the most covered by analysts, it is relevant to consider that empirical research shows that firms with more analyst coverage, less variable earnings streams, and lower absolute analyst forecast error tend to have lower cost of capital (Gebhardt, Lee & Swaminathan, 2001).

We would prefer to simply use the WACC estimated by Morningstar for each company, so there would be no difference between the WACC utilized in Morningstar's valuations and our quantitative valuation models. This data, however, has not been available, as the WACC estimates can only be found in the individual valuation models for each stock. Instead, the following three methods have been applied.

The primary method is based on a random sample of Morningstar's estimated WACC for 10 companies in each Morningstar Sector and compute averages of the 10 sectors; Technology, Consumer cyclical, Healthcare, Energy, Communication services, Consumer defensive, Industrials, Basic materials, Utilities, and Real estate. The samples were taken in January 2019. The advantage of estimating WACC this way is that we come closer to the individual company WACC applied in Morningstar's valuations, thus limiting the importance of WACC when we compare the performance of our valuation models to Morningstar's.

Secondly, we test the impact of applying the industry WACC calculated by Damodaran from NYU Stern School of Business (Damodaran, 2019) and aggregate these on the 10 sectors described above. We take a simple average of the industries that we categorize under the 10 Morningstar sectors. Thirdly, we take the consensus sector WACC estimates of all U.S. stocks from Bloomberg on the 18th of January 2019. **Table 3.1** below compares the resulting sector costs of capital.

Figure 3.1: Sector WACC from Morningstar, Bloomberg, and Damodaran (NYU)

	Morningstar sample WACC	Bloomberg WACC	Damodaran (NYU) WACC
Technology	9.00%	10.35%	11.40%
Consumer cyclical	8.72%	8.65%	10.41%
Healthcare	7.09%	10.16%	11.33%
Energy	8.21%	9.37%	11.81%
Communication services	8.23%	9.05%	10.24%
Consumer defensive	7.35%	7.67%	10.95%
Industrials	8.37%	9.66%	11.05%
Basic materials	8.24%	8.99%	11.85%
Utilities	6.39%	5.18%	8.40%
Real estate	7.54%	6.99%	9.58%

The table illustrates a comparison of WACC between Stern, Bloomberg and Morningstar on a sector level.

Source: Own estimation, Morningstar Direct, Bloomberg Terminal & Damodaran (NYU).

WACC estimates from Bloomberg are generally higher than Morningstar's, and Damodaran's estimates are even higher than Bloomberg's. Applying lower costs of capital will result in higher valuations and vice versa. We expect that Morningstar's WACC is lower because it is only based on samples of stocks in the S&P 500, which are generally larger, more stable businesses of higher quality that should demand a lower equity premium and cost of debt relative to the market as a whole. However, we have found S&P 500 companies to have higher market beta (systematic risk) than the overall U.S. market (see Section 4.2). Higher beta should demand a higher equity risk premium according to the CAPM (Sharpe, 1964). According to Morningstar (2015), revenue cyclicality, operating leverage and financial leverage are key factors in their estimates of systematic risk and cost of equity (see **Section 2.3**).

Growth (g)

Growth in the perpetuity formula is an important factor, as it determines how FCFF is expected to grow in all future years. For this reason, the assumed growth should represent a normalized steady-state level and reflect any productivity improvements a company can generate infinitely. The idea behind calculating terminal value is partly that the growth rate of a company should eventually converge towards the growth rate of the economy, that the company operates in (Plenborg, Petersen & Kinserdal, 2017, p. 302). In theory, the steady-state growth must not exceed the long-term growth rate of the economy. If this is the case, the company will eventually grow larger than the economy itself. As a result, the starting point of the growth estimate should be the long-term nominal growth of the economy. In fact, it would make sense to assume a company's steady-state growth to be a bit lower than the economy's because new entrants are introduced and contribute to the growth. For very large companies in declining industries, and for companies that pay out much of their earnings instead of reinvesting it, growth should be expected to be lower. The relevant economy to consider is often the local economy, but since many companies are global, the global economy-wide growth can be more relevant.

Nissim (2017, p. 29) suggests two ways of estimating the long-term economy-wide growth. The first approach estimates the long-term nominal growth by adjusting the real growth forecasts of economists by expected inflation, as follows:

$$Long - term\ nominal\ GDP\ growth = (1 + LTG) \times (1 + LTI) - 1$$

LTG: Long-term real GDP growth
LTI: Long-term inflation rate

The long-term real growth and inflation forecasts in the U.S. can be obtained from FRED (2018).
Long-term real GDP growth (2021): 1.75%
Long-term inflation (2021): 2.05%

By applying these estimates, we can calculate the long-term economy-wide nominal growth based on economist forecast below. This estimate will be the primary growth input in our valuation models throughout the analysis in **Section 4**.

$$Long\ term\ nominal\ GDP\ growth = (1 + 1.75\%) \times (1 + 2.05\%) - 1 = 3.84\%$$

The second method is the interest rate approach. Here, the growth is forecasted based on the long-term risk-free rate. The rationale of this approach is that the long-term risk-free rate is approximately equal to the expected inflation plus the real interest rate. In turn, the real interest rate is the key component of real returns in the economy, which helps to drive economic growth (Nissim, 2017, and Nissim, 2017A).

These two ways of determining the long-term growth have a correlation of 0.82 (Nissim, 2017), but typically the long-term nominal GDP growth tends to be substantially higher than the long-term risk-free rate. This difference is partly due to upward bias from economists forecast and partly due to risk premiums. Real returns are likely to be higher than long-term risk-free rates since capital providers require risk compensation (Nissim, 2017).

Nissim (2017) determines the risk-free rate as the 5- and 10-year forward rates, which are determined from the 5- and 10-year spot rates. The spot yields are determined by deducting corresponding credit default swaps from the 5- and 10-year government yields (Nissim, 2017). A simpler way to determine the risk-free rate is the yield on the long-term treasury bond with 20 years to maturity (Kaplan & Ruback, 1995). According to Nissim (2017) there are three main advantages of using the long-term interest rate instead of nominal GDP growth:

1. WACC minus growth will never be too small since the long-term interest rate is essentially the minimum required return. WACC is essentially the long-term risk-free interest rate plus a premium.
2. The long-term interest rate is not sensitive to errors in identifying the relevant economy, because the two main determinants of the economy's long-term growth (expected inflation and real return) cancel out in the WACC minus Growth denominator in the terminal value formula.
3. Forecasts from economists of inflation and growth are biased and only available for the near future. The forecasts are likely affected by the current stage of the business cycle.

Another approach of estimating a nominal growth rate in the terminal cash flow is to take a recent five year average inflation sample and add a real growth rate between 0% and 1% (Kaplan & Ruback, 1995).

Other simpler approaches to determine growth in steady-state is to apply an ad-hoc growth of either zero percent or the nominal inflation rate (e.g., Francis et al., 2000, and Frankel & Lee 1998). In our analysis in **Section 4**, we will stress the performance of our valuation models by applying a 6% and a 0% growth rate, to observe how robust the performance is.

We could also simply take the average historical growth rate. The average nominal GDP growth from 1930 to 2017 have been around 6.35% (The Balance, 2018). But because more recent numbers are more relevant, and because inflation has been much more modest in the past decades, we would expect nominal growth of the U.S. economy to be lower than in the last 87 years. For these reasons, we also test the impact of a growth rate of 3.95%, which has been the average nominal growth from 2003-2017.

Summing up, the three growth rates that we will emphasize in our valuation models are:

1. Real GDP growth forecast from economists: 3.84%
2. 20-year treasury rate: 2.83% (US department of treasury, 2018)
3. Average real GDP growth from 2003-2017: 3.95%

Net interest bearing debt (NIBD)

Net interest bearing debt is a company's total interest bearing debt (such as bank loans, mortgages, and capital lease obligations) less any cash, securities, or other liquid funds that could be used to pay down the debt. In other words; financial liabilities minus financial assets. As explained in the theoretical framework, net interest bearing debt is determined to calculate the value of a company on a debt free basis.

The correct approach to calculating net interest bearing debt is to go through all assets and liabilities and determine for each item whether they are operating or financial (interest bearing) for each company individually (Plenborg, Petersen & Kinserdal, 2017, p. 114). Due to varying company characteristics, the different items on the balance sheet are not always determined the same way. Some can be either or, why the judgement of whether an item is operating or financial can be challenging. With this in mind, we need to come up with a quantitative proxy for the net interest bearing debt that we can apply across all firms in the S&P 500. Nissim (2017) suggests calculating the net interest bearing debt as follows:

$$NIBD = Debt - Financial\ Assets$$

Here, debt is both the long- and short-term debt added together, and the financial assets are financial instruments that do not contribute to the operating profit, this could be cash and cash equivalents, securities, real estate investments etc. (Nissim 2017, p. 46). However, this proxy would forego capital lease obligations and employee pension liabilities that might constitute a significant chunk of the balance sheet.

Kaplan & Ruback (1995) determine NIBD in a similar manner:

$$NIBD = Long\ Term\ Debt - Cash\ \&\ Cash\ Equivalents$$

The problem with the approach from Kaplan & Ruback is the assumption that short-term debt is operational and non-interest bearing, but current loans, notes payable and the current portion of long-term debt are often a significant portion of the interest bearing debt.

With the data from Morningstar Direct available, we compute NIBD as follows:

$$NIBD = Long\ Term\ Debt\ \&\ Capital\ Lease\ Obligations + Current\ Debt\ + Preferred\ Stock - Cash\ \&\ Cash\ Equivalents - Securities - Short\ Investments$$

The formula above corresponds to Nissim (2017) but also adds capital lease obligations, since these are interest bearing (Sørensen, 2012, p. 160), and preferred stock. The estimate of financial assets includes items such as cash and equivalents, marketable securities held for sale or until maturity and short-term investments (maturity between 3 months and 1 year). This implicitly assumes that the firm can use all these funds to pay back debt without affecting their operations, although some liquid funds are always needed if the firm should suddenly be in need of cash (Nissim, 2017a, p. 20). The formula implicitly assumes that employee pension liabilities are operating in nature although some firms estimate these at fair value (Sørensen, 2012, p. 178). We have analyzed the impact on a sample of our valuations, if pension liabilities are classified as a financial liability, and the impact is not material.

Free cash flow to firm (FCFF)

The discounted cash flow model is the most used model for practitioners and in business schools (Plenborg, Petersen & Kinserdal, 2017, p. 299 and Penman 1998). FCFF represents a company's ability to pay dividends, repurchase shares and pay back debt. An important detail for the DCF model regarding the terminal period is that the free cash flow has reached a steady-state level when estimating the terminal value. Especially because the terminal value accounts for 60-80% of the total value in a DCF (Plenborg, Petersen & Kinserdal, 2017, p. 303).

The free cash flow can be calculated in the following way (Abrams, 2000):

$$FCFF_t = Cash\ from\ operations_t - Cash\ from\ investments_t$$

The measure above is the input in our primary Gordon Growth models. Cash from operations and investments can be found in Morningstar Direct and reflect the numbers reported in each company's annual report (10-K). Because we apply unadjusted numbers, cash from operations and investments might include financial items such as cash generated from selling securities, if the individual company reports this as a part of cash from investments.

The fundamental driver of enterprise value is the operating free cash flow, which is the cash flow generated from the operations of the firm - including investments made to sustain or grow operating assets but ignoring all cash flows related to the financing of the company.
Examples of what should be excluded from the company's operating free cash flow is the following: financial items, financial lease payments, interest received on cash holdings, repayments of debt, new issue of debt or equity, dividend and share repurchases. Any corporate tax which is associated to the financial cash flows of a company should also be excluded. The point is to have a clear view of what the company is worth if it is only equity financed and has no surplus cash (Cooper, 2016, p. 2).

Ian cooper (2016) suggest the following way to calculate the free cash flow:

$$FCFF_t = Cash\,from\ \ operating\ activities_t\ - Cash\,from\,investing\ activities \\ + Net\ interest\ \times\ (1 - Tax\ rate)$$

The net interests after taxes are added because the calculation of operating cash flow in a company's statement of cash flows usually starts with net income, where interests after taxes have already been deducted. The tax rate should, according to Cooper (2016), be the statutory tax rate, not the effective tax rate. Since a firm with positive net income has incrementally saved tax at the statutory rate. If there have not been any interest expenses, the tax bill would have been higher (this is also known as the tax shield). For this reason, NOPAT should be used to determine FCFF, and the formula can be written as:

$$FCFF_t = NOPAT + Depreciation\ -\ CAPEX - Increase\ in\ operating\ working\ capital \\ +/-\ accrual\ adj.$$

Because FCFF can be affected by transitory items, the estimate should be further normalized. This, Cooper (2016, p. 16) suggests doing in the following steps:

1. Exclude abnormal items; We only want items to be represented, which are not transitory and unlikely to be repeated.
2. Adjust to be consistent with the middle of the business cycle: Cash flows varies across business cycles and we want a stable level to represent the cash flow in steady-state. Cooper (2016) suggests that the easiest way to normalize FCFF is to average it over a business cycle. This method works for relatively mature firms, but it can create problems for growing companies where it is suggested to normalize the cash flow through an average of the EBIT margin over the business cycle and then estimate the cash flow based on the margin.

FCFF can also be calculated as:

$$FCFF_t = NOPAT + change\ in\ invested\ capital$$

See **Section 3.2** for our definition of invested capital. We have tested how large the impact is on our valuations by applying both reported FCFF and the measure outlined above. The two measures do not result in considerably different performance as seen in **Appendix 3**. To understand the extent of the implication, we made a sample test of 50 firms in the S&P 500. We found that 30 of the firms calculate their cash from operations based on net income, and 26 of the companies have different kinds of financial transactions as part of their cash from investments. Examples of these are: purchase and proceeds of marketable securities, gains from equity investments, financing receivables etc.

Gordon Growth Valuation Models

In this thesis 3 different approaches have been applied to estimate FCFF:

1. The first approach is simply to estimate the value of the company by assuming last year's reported free cash flow to grow in perpetuity. We will refer to this model as *LY FCFF*:

$$Equity\ value_t = \frac{FCFF_{t-1} \times (1+g)}{WACC - g} - NIBD_t$$

2. The second approach is to determine the steady-state free cash flow by taking the 3-, 5-, and 10-year average of reported FCFF. We will refer to these models as *3Y Avg.*, *5Y Avg.*, and *10Y Avg.*:

$$Equity\ value_t = \frac{\frac{1}{n}\sum_{i=1}^{n} FCFF_i \times (1+g)}{WACC - g} - NIBD_t$$

3. The third approach is to normalize the free cash flow with an EBITDA conversion ratio. We determine the 3-, 5-, and 10-year historical ratio between EBITDA and reported FCFF by taking the median of the conversion ratios over the different periods. We will refer to these models as *3Y Norm*, *5Y Norm*, and *10Y Norm*:

$$Conversion\ ratio_t = \frac{FCFF_t}{EBITDA_t}$$

$$Equity\ value_t = \frac{(Median\ Conversion\ Ratio \times\ EBITDA_t) \times (1+g)}{WACC - g} - NIBD_t$$

All the valuations suffer from the fact that they are all based on historical cash flows, and past results are no guarantee of future performance. We also note that Plenborg, Petersen & Kinserdal (2017, p. 94-95) found that free cash flows are not able to effectively predict market price movements.

Last year FCFF is the simplest of the four methods and easy to apply. The last year FCFF is implying that the best estimate of future free cash flow is the FCFF generated most recently, which is in line with the assumption that recent numbers are more predictive than older numbers (Nissim, 2017, p.16). This estimate does not consider how the company has performed through business cycles. It can be impacted by one-off transactions, that are not part of the company's core operations and will not impact the performance on a recurring basis. Events such as larger acquisitions, divestments, investments or lawsuits can over- or understate FCFF and have a major impact on the value of the company in perpetuity. The upside of this model compared to the others is that it favors companies with strong recent performance such as companies that have grown their cash flows or have been through a turnaround.

The second line of models is the 3-, 5-, and 10-year average FCFF. The 10-year average is applied to come up with an estimate of a realistic steady-state level of free cash flow, which takes a whole economic cycle into account. This should be a more realistic assumption because the steady-state FCFF should reflect how a company performs over a whole business cycle, both in recessions and booms, since we assume that these cycles will repeat themselves. One of the implications with a 10-year average is that it does not take into account if a company has been through some kind of major change in this 10-year period. An example of this could be a firm that has matured recently and not been able to produce positive cash flows earlier. This company's future FCFF could remain positive and stable but that will not be reflected in a 10-year average. The impact of this problem will presumably be that younger and fast-growing companies will not be considered as attractive as those that have generated positive free cash flows for a long period. The 3- and 5-year average FCFF models capture less of the business cycle, but they reduce some of the problems stated about the 10-year average model. On a positive note, these three models are relatively simple, they take historical performance into account, and the procedure is easy to understand.

The third line of models are more sophisticated and apply a normalizing factor. The point is to estimate how much of earnings before interest, taxes, depreciations, and amortizations (EBITDA) that the company has been able to convert into free cash flows historically. We then convert last year’s EBITDA into an estimate of steady-state FCFF by multiplying with the conversion ratio because of the rationale that the income statement, due to accrual accounting, is less volatile than the cash flow statement. The conversion ratio is calculated by dividing each year’s FCFF by EBITDA. We then take a 3-, 5- and 10-year median of the past conversion ratios. We opt for a median instead of an average because it limits the effect of outliers.

We test three different variations of the valuation model with a 3-, 5-, and 10-year normalized cash flow, due to the dilemma that most recent numbers have more explanatory power (Nissim, 2017, p. 16), while longer-term fundamentals consider more of the cycle and favor stable businesses. These models should be better at determining the value of growing firms because we apply last year's EBITDA. Yet, they struggle when firms have recently improved their ability of converting EBITDA into free cash flows (perhaps because large investments are no longer necessary), as such firms will have a low median conversion ratio.

We wondered if we should use EBIT or EBITDA for estimating the conversion ratio. We settled on EBITDA. When we stress the performance measures of the three normalized valuation models by applying EBIT instead of EBITDA, we get slightly higher Sharpe ratios on the 5- and 10-year normalized FCFF portfolios, but there is generally no noteworthy impact (**Appendix 20**). Nissim (2017a, p. 10-15) presents the arguments for and against deducting depreciation and amortization to determine a company's operating income. The arguments for and against EBIT and EBITDA are stated below.

Arguments for EBITDA

EBITDA has become increasingly popular to use when approximating cash flows, as it is believed to be more closely related to the firm's operating cash flows, and because EBITDA is not affected by differences in depreciation and amortization policies (Plenborg, Petersen & Kinserdal, 2017, p. 96).

The first argument is that the timing of asset purchases varies across companies and this makes the reported earnings deviate from economic earnings. If one company has recently made a large investment will also have larger depreciations, whereas another company waiting to make the same investment next year will have lower depreciations and higher EBIT. This reduces earnings comparability between companies.

The second argument is that because the average age of assets varies over time, so does the magnitude of depreciations. This reduces the comparability of EBIT between companies with assets of different ages. Depreciations also enables earnings management because depreciations and amortizations allow accounting flexibility and requires some subjective judgements from management in terms of the useful lives, salvage values, and impairments of assets, how to measure their costs and to decide whether they should be subject to amortization.

The third issue according to Nissim (2017a) is that companies might include financing costs in depreciations, because assets that require a long construction period (such as plants and property) may include interests on lending during the construction period. The rationale is that the benefits from borrowing will be realized in future years when construction is complete. The problem is that the interests paid are added during the assets construction and expensed through depreciations when the assets are being used for operations. This way, EBIT would also contain financial expenses and not only operating expenses.

In terms of the explanatory power of multiples, Nissim (2017a) comes to the conclusion that EV multiples with EBIT, EBITA or EBITDA are all good for explaining future stock prices. However, EBITDA performs better than EBIT and EBITA, and EBITA performs better than EBIT. He also finds that the difference between the explanatory power of EBITDA and EBITA narrows down since the early years of the 21st century and particularly after the financial crisis (Nissim, 2017a, p. 3). Thus, we could also consider applying EBITA in our conversion ratios.

Arguments for EBIT

EBIT includes depreciations and amortizations which represent the cost of assets used by the firm. Instead of expensing the upfront payment of an asset immediately before it has delivered any benefits to the business, depreciations distribute the cost of the asset over its' estimated lifetime. Even though many would argue that depreciations are non-cash items, these are part of smoothing out earnings over time. Although EBITDA includes the cost of labor, it excludes the cost of fixed assets. Since some businesses are asset intensive instead of labor intensive, EBIT could be argued to provide a better comparison.

EBITDA is more sensitive than EBIT to a specific type of earnings management called "excess capitalization of expenditures". This could be when a company increases its net income by moving costs to the balance sheet instead of the income statement. According to Nissim, excess capitalization is primarily related to property, plant and equipment and intangible assets. An example could be a manager who classifies general training in the use of a new machine as part of the expenditures of the machine itself - thus capitalizing the expense on the balance sheet and depreciating it over time. The cost of excess capitalization will impact EBIT in future periods as part of depreciation and amortization, but it will not be reflected in EBITDA.

3.2 McKinsey's Value Driver Formula

As an alternative to the Gordon Growth models, this section describes a quantitative valuation model based on the value driver formula presented by McKinsey (2015, p. 31). The advantage of this model is that it illustrates the relationship between growth, free cash flow and returns on invested capital. To grow, a company must invest - especially if it is a capital-intensive business. This relationship exposes how slowing growth assumptions can have a significant positive impact on free cash flow because less cash must be reinvested in the business.

$$Continuing\ Value_t = \frac{NOPAT_{t+1} \times (1 - \frac{g}{RONIC})}{WACC - g}$$

NOPAT: Net operating profit after taxes. McKinsey (2015, p. 31) apply NOPLAT (net operating profit less adjusted taxes). Later, we will explain why.
g: growth of NOPAT in all future periods.
RONIC: Return on new invested capital, or rather, the return on the next dollar invested.
g/RONIC: Defines the investment rate (IR) or the portion of NOPAT reinvested in the business.

With Gordon's Growth formula, analysts are prone to ignore the link between growth and free cash flow. If the growth assumption in steady state is lower than the growth at the end of the explicit forecast period (which it often is), it should not be necessary for the firm to keep reinvesting the same portion of its operating income, and this would make the free cash flow higher. If steady-state FCFF is based on the most recent fiscal year (as we do in one of our Gordon Growth models) or is based on the cash flow in the final year of an analyst's explicit forecast period, the FCFF in perpetuity can often be too low and underestimate the terminal value significantly (McKinsey, 2015, p. 250).

When assuming a lower growth in the value driver formula, the investment rate (g/RONIC) will decrease while the cash flow (NOPAT × (1 - g/RONIC) will increase. For this reason, the value driver formula can prove superior when companies have not yet reached steady state. Morningstar applies a similar formula when calculating terminal value but always assumes RONIC to equal cost of capital (WACC). This implies that all new investments and growth will not generate any value, which deletes growth and the investment rate from the formula (see **Section 2.3**).

NOPAT and tax

Net operating profit after tax (NOPAT) is computed as follows:

$$NOPAT = EBIT \times (1 - tax\ rate)$$

McKinsey's NOPLAT also adds the change in deferred taxes and excludes amortizations by using EBITA instead of EBIT. To avoid large year-to-year fluctuations in deferred taxes, that might affect our steady-state estimates, we apply NOPAT. Using EBIT instead of EBITA means that amortizations of acquired intangibles are also subtracted from operating profit, but McKinsey (2015, p. 393) argues that such noncash expenses should be excluded. The argument is that only acquired intangibles are capitalized and amortized, whereas internally developed intangible assets, such as brands, are expensed as SG&A when they are created (due to accounting standards). Thus, if a company acquires an intangible asset and then replenishes the asset through internal investments, its EBIT will be penalized twice; once through selling, general, and administrative expenses (SG&A) and again through amortization (McKinsey, 2015, p. 393).

Yet, we would like to point out that this argument goes both ways, and EBITA can also overstate operating profit. Excluding amortizations would favor companies where acquiring brands, patents or client relations is a consistent part of the business as an alternative to developing these assets internally. Big pharma is an example where mergers and acquisitions are a consistent part of operations, and where acquired patents become recognized on the balance sheet. In such cases, EBITA will not be penalized by amortizations, and at the same time, SG&A will appear lower because intangibles are purchased externally instead of being developed internally and expensed (Nissim, 2017a, p. 17). In this case, EBITA would overstate operating profit.

When estimating both free cash flows and operating profit, investments are necessary not only to maintain existing assets but also to grow. In this context, depreciations can be seen as a proxy for the cost of maintaining the existing asset base (Nissim, 2017a, p. 12). In the same way, amortizations approximate the cost of maintaining intangible assets (if the value of brands and patents erode over time). Since companies can determine whether to replace their assets this year or the next, excluding depreciations and amortizations could be optimal in the near term. But for estimating long-term profitability and free cash flows - which we strive to do in our terminal value models - D&A should not be ignored (Nissim, 2017a, p. 12). In the end, whether EBITDA, EBITA or EBIT best describe operating profit depends on the individual firm, but since we do not have the luxury of making such individual distinctions in a quantitative model, we lean towards EBIT for the reasons listed above.

It is challenging to estimate the tax rate on operating income. A common approach, which we follow, is to apply the effective tax rate (the ratio of the income tax expense to earnings before tax) as follows:

$$Tax\ rate = \frac{Income\ Taxes}{Earnings\ before\ tax\ (EBT)}$$

The effective tax rate represents the weighted average tax rate on operating income and other items included in the earnings before tax such as interest income/expenses. If the tax on these items is different than on the operating profit, the effective tax rate can be a poor proxy (Nissim, 2017, p. 39). Transitory items such as unrecognized tax benefits, unreserved prior periods tax payments and changes in tax rates contribute to the volatile nature of the effective tax rate (Nissim, 2017, p. 40).

An alternative would be to apply the marginal federal and state tax rate in the U.S. such as Kaplan & Ruback (1994, p. 9) in each given year, but the S&P 500 constituents are mostly international firms with operations all over the world that typically pay lower tax rates on foreign earnings (McKinsey, 2015, p. 380). Using the same tax rate across firms would also eliminate the fundamental differences that allow some industries to benefit from R&D tax credits or the ability to optimize their tax efficiency by placing operations and assets in low-tax countries.

In our model, we apply the effective tax rate on EBT for simplicity. If the tax rate is larger than 50% or lower than 10%, which we interpret as unsustainable in the long term, we ignore this value and instead apply a median historical tax rate of up to 5 prior years.

We apply the most recent fiscal year's NOPAT but also test historical averages of NOPAT as an input in the value driver formula. A historical average would have a negative effect on the valuation of growing businesses and high-growth sectors such as technology, since their historical operating profits are typically lower than their current.

Since we apply a raw, unadjusted EBIT we will not risk overstating steady-state NOPAT by excluding "one-time" losses such as impairments and restructuring costs, which are not commonly forecasted by qualitative analysts - although these items can sometimes be recurring in nature (Nissim, 2017, p. 27). Special items are most often negative (Johnson, Lopez & Sanchez, 2011), so excluding them will often result in higher operating profits. Since we do not exclude special items, we run the risk of understating the operating profit of the continuing business - resulting in lower valuations. In the case of large positive special items, we may risk overestimating steady-state NOPAT by not excluding them.

Invested Capital
To compute returns on new invested capital (RONIC), we must determine a quantitative proxy for invested capital with the data points available in Morningstar Direct. As we have already estimated NIBD in **Section 3.1**, we can compute invested capital as the net financing (or capital) on the right-hand side of the balance sheet (Sørensen, 2012, p. 159):

$$Invested\ Capital = Net\ Interest\ Bearing\ Debt + Total\ Equity$$

Total equity includes minority interests. One important item to outline is goodwill, which is implicitly included in our proxy of invested capital. This is consistent with also including goodwill impairments in NOPAT. The formula above should be identical to the net assets approach on the left-hand side of the balance sheet, where operating liabilities are subtracted from operating assets (Callahan & Mauboussin, 2014). The net assets approach is preferable in practice but harder to determine quantitatively with the data points available in Morningstar Direct.

Return on new invested capital (RONIC)
RONIC can be measured as:

$$RONIC = \frac{NOPAT_t - NOPAT_{t-1}}{Invested\ capital_t - Invested\ capital_{t-1}}$$

RONIC determines the marginal operating profit after tax as a percentage of the marginal capital invested in a given period. RONIC measures the returns generated when a company invests its capital to create new value from core operations.

The expected future RONIC should be consistent with the firm's competitive environment (McKinsey, 2015, p. 250). Economic theory suggests that competition will erode and eliminate any abnormal returns over time. This would be an argument for assuming steady state RONIC to equal WACC in competitive industries. If the return on new investments is equal to the capital costs, then growth will not be value accretive but instead value neutral with a net present value of zero. Higher growth will increase NOPAT but is offset by larger investments. Over time, this will dilute the return on invested capital (ROIC) until it reaches WACC (McKinsey, 2015, p. 262). Making such an assumption in the long term can be reasonable but might be overly conservative in a single-period valuation model - especially for firms with sustainable competitive advantages such as network effects, brands, or patents not captured on the balance sheet as argued by McKinsey. Similarly, asset-light operating models can demand long-term sustainable and high returns on invested capital above the level of WACC, because the amount of invested capital on their balance sheet is lower.

Due to the marginal changes from year to year, the nature of RONIC have been very volatile in our dataset over time. For this reason, applying a historical RONIC in the terminal value formula is not ideal for stable valuations. RONIC is greatly influenced by noise when large investments take place, and the increased profits as a direct consequence of new investments may take years to materialize. The immediate effect of new investments on operating profit can also be severe due to straight line depreciations. Qualitative assessments by equity analysts such as RONIC converging (fading) towards WACC over time or assuming a level between a firm's current ROIC and WACC in a competitive advantage period (CAP) can prove valuable depending on the individual firm in question (Mauboussin & Johnson, 1997). But for a quantitative approach, we will instead look towards ROIC, which is a more stable measure of profitability, or we will simply assume RONIC to equal WACC in one of the variations of our value driver models.

Return on invested capital (ROIC)

Return on invested capital (ROIC) can differ materially from RONIC due to the law of diminishing returns, competition and attractive investment opportunities becoming scarcer over time. Starbucks' flagship store in Seattle might for example drive attractive returns (ROIC) for many years to come, but as it becomes more and more difficult to find new attractive locations, the return on new stores over time (RONIC) will decline. Still, due to the volatile nature of RONIC and for simplicity, we will apply a less conservative assumption; that a firm's RONIC becomes equal to its historical ROIC in the value driver formula.

ROIC is a key driver of terminal value, and recent research has indicated that median ROIC over a business cycle dominates the firm's current ROIC at predicting steady-state profitability (Nissim, 2017, p. 22). Companies earning high returns tend to experience gradually falling ROIC over the succeeding 15 years, while companies earning low returns tend to see them rise over time - thus exhibiting some mean reversion (McKinsey, 2015, p. 110 and Nissim, 2017, p. 17). According to the studies mentioned, the best performing companies can generally sustain their abnormal returns for more than 10 years. Thus, assuming ROIC to approach WACC in valuations is overly conservative for the typical company with sustainable competitive advantages.

The ROIC of individual companies also trends toward their industry medians over time but is relatively persistent (McKinsey, 2015, p. 105). A historical median of industry ROIC tends to be superior when forecasting steady state profitability in comparison to a firm's current ROIC, historical median ROIC and the industry's current ROIC (Nissim, 2017, p. 22). However, this result, is most evident in the longer term with more than three years of explicit forecasts (with terminal value estimated as of T = 3). Since the valuation models in this thesis calculates an immediate terminal value with no explicit forecasts, these results might indicate that applying median industry ROIC is less advantageous. We've decided to keep it simple and not apply industry ROIC in our quantitative valuation models.

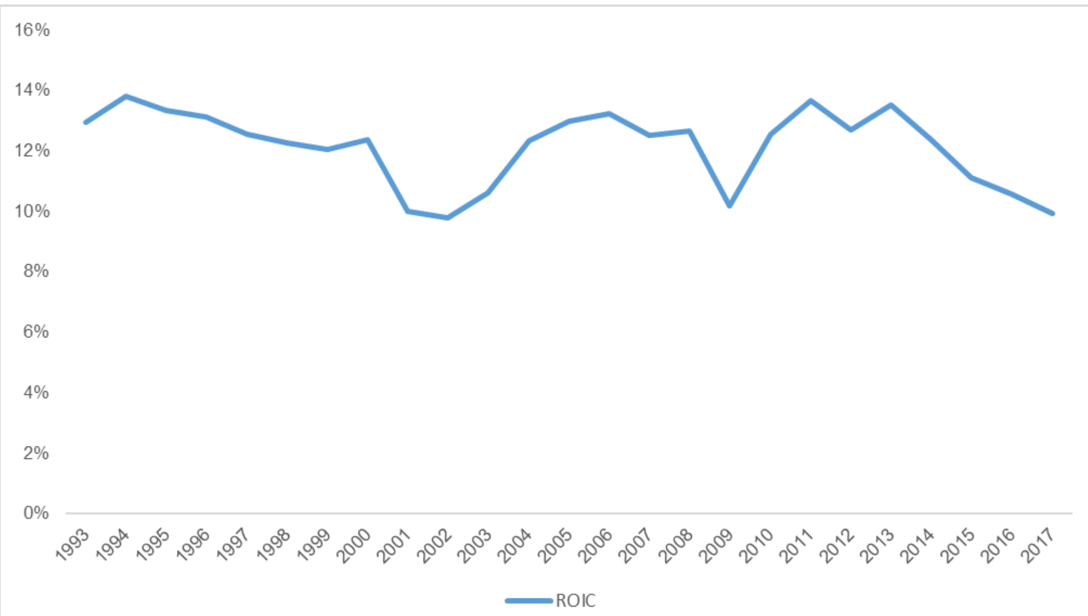
However, since we utilize 10 different sector-WACC in our valuations, we will be setting RONIC equal to the sector WACC in one of our value driver models. We estimate ROIC as follows:

$$ROIC = \frac{NOPAT}{(Invested\ Capital_t + Invested\ Capital_{t-1})/2}$$

By using the average invested capital at the beginning and end of the year as stated in the formula, we arrive at a more precise estimate of the return on invested capital across a whole fiscal year (Plenborg, Petersen & Kinserdal, 2017, p. 142-148).

The estimated ROIC on the constituents of the S&P 500 is mostly not a volatile number from one year to another and outliers are rare. The estimate is quite stable but with a downward trend since 1993 which corresponds with the erosion of competitive advantages and abnormally attractive investment projects over time (McKinsey, 2015, p. 250). This is illustrated in **Figure 3.1** below. Due to this trend, using a historical median of a company's ROIC will tend to yield a higher fair value compared to simply applying ROIC from the last fiscal year in our data sample. Since ROIC also exhibits some clear signs of cyclicality (consistent with prior research by Nissim, 2017, p. 17) during the Dot-com bubble and financial crisis, these observations can offset this effect.

Figure 3.1: Returns on invested capital (ROIC) of the S&P 500 companies from 1993 to 2017



Median returns on invested capital (ROIC) of the S&P 500 constituents excluding financials from 1993 to 2017. Goodwill is included.

Source: Morningstar Direct and own estimations.

The results above are contrary to what McKinsey (2015, p. 104) found, which was a stable median ROIC from 1963 until the early 2000s at about 10% and an increase to 16% towards 2013. One might suspect that McKinsey's sample would not only include large U.S. companies, such that smaller, fast growing companies and creative destruction could play a role in offsetting the lower returns of larger and maturing firms - but this is not the case. McKinsey utilized a comparable dataset of over 1.000 U.S.-based nonfinancial companies with revenues greater than $1 billion to sort out small companies. So the different results should not be due to a size difference. Rather, the primary explanation is the included goodwill in our estimate of invested capital. The accumulated goodwill from M&A activity has significantly impacted the returns on invested capital negatively of the large U.S. firms since 1992 (McKinsey, 2015, p. 112). Consequently, by including goodwill in ROIC, our valuations will be lower – especially for stocks that have carried out large acquisitions and accumulated goodwill on their balance sheets.

Summing up, future returns on invested capital should either move towards a common industry level, trend towards cost of capital (WACC) or remain close to a company-specific through-the-cycle level.

Valuation methods

To perform a quantitative valuation with the value driver formula, we have applied 4 different methods to estimate the inputs in the numerator. We test several variations of these to show that our results are robust across the different measures.

1. In the first and most basic value driver model, we estimate the equity value of firms by assuming last year's NOPAT to grow in perpetuity while returns on new invested capital equal their sector's cost of capital (WACC). We refer to this model as *RONIC=WACC*.

$$Equity\ value_t = \frac{NOPAT_{t-1} \times (1 + g) \times (1 - \frac{g}{RONIC = WACC})}{WACC - g} - NIBD_t$$

2. In a second, less conservative, model we estimate the equity value by assuming last year's NOPAT to grow in perpetuity, and that the company can conduct new investments at the same return as last year's ROIC. We refer to this model as *LY ROIC*.

$$Equity\ value_t = \frac{NOPAT_{t-1} \times (1 + g) \times (1 - \frac{g}{ROIC_{t-1}})}{WACC - g} - NIBD_t$$

3. In the third model we assume last year's NOPAT to grow in perpetuity and that the firm's return on new investments equal a median historical ROIC. We perform tests with 3-, 5-, and 10-year medians of ROIC. We refer to these models as *3Y median ROIC*, *5Y median ROIC* and *10Y median ROIC*.

$$Equity\ value_t = \frac{NOPAT_{t-1}\ \times\ (1\ +\ g) \times\ (1 - \frac{g}{Median\ \ ROIC})}{WACC\ -\ g} - NIBD_t$$

4. The fourth approach is to estimate the steady-state NOPAT as a historical average while applying a historical median ROIC as a proxy for the steady-state return on new invested capital. We test the efficacy of 3-, 5-, and 10-year average NOPAT and median ROIC. We refer to these as *3Y Average NOPAT*, *5Y Average NOPAT*, and *10Y Average NOPAT*.

$$Equity\ value_t = \frac{\frac{1}{n}\sum_{i=1}^{n} NOPAT_i\ \times\ (1\ +\ g) \times\ (1 - \frac{g}{Median\ ROIC})}{WACC\ -\ g} - NIBD_t$$

A common feature of the value driver models described above is that the fundamental inputs are based on past financial performance and not subjective forecasts. The most recent year's NOPAT is applied in the first three models due to being more relevant (Nissim, 2017, p. 16) and is relatively robust when adjusting for unusually large, small, and negative tax rates as described above.

In addition to being theoretically more valid and realistic to assume steady state RONIC equal to WACC in the first value driver model, it is also a conservative assumption for firms earning returns above their cost of capital while being an aggressive assumption for firms earning lower returns on capital. A single-period valuation is already quite conservative for fast growing companies with moats by assuming a low constant growth and not having an explicit forecast period or a prolonged period of sustained competitive advantages before steady state is reached (McKinsey, 2015, p. 256). Such qualitative valuation maneuvers would normally act as a runway for growth and increasing profitability before finally calculating terminal value. As a result, the RONIC=WACC model should not provide very attractive or precise valuations of fast-growing companies that have not yet matured but might only be suitable for stable and mature firms (McKinsey, 2015, p. 144). As we will illustrate later, relatively few firms are typically deemed undervalued by the first model compared to the others. Since we apply the same WACC to every company in a given sector, the assumption of RONIC to equal WACC will over time move the overall profitability (ROIC) of all firms within that sector to a common level. As these firms grow and make new investments with identical RONIC, this will gradually dilute the companies' overall ROIC and make it converge towards the assumed sector WACC.

In the second and third model we try to compensate for the conservative nature of the single-period valuation by assuming some less conservative inputs. We assume the return on new investments (RONIC) to be equal to a median of the firm's 3-, 5-, or 10-year ROIC or simply the last year's ROIC. This allows high-quality firms with competitive advantages and abnormal profitability to sustain these levels forever - subsequently increasing their terminal value. On the other hand, firms which have historically earned a ROIC below WACC, will not see their returns on capital rise to a value-neutral point (as our first model assumes). Instead, we assume these firms to stay the course and forever destroy shareholder value when they invest and grow (McKinsey, 2015, p. 22). Thereby, applying historical levels of profitability can prove a double-edged sword by overrating quality metrics and undervaluing junk stocks as defined by Pedersen, Asness & Frazzini (2013), although empirical studies indicate that profitability is sticky over time (McKinsey, 2015, p. 110 and Nissim, 2017, p. 17). A benefit of utilizing a historical median of ROIC is that these studies also point towards returns on capital exhibiting mean reversion over time. A longer-term median will also reflect the returns on capital through a whole economic cycle and include events of low returns such as The Great Recession and the Dot-com bubble.

In the fourth model we assume steady state NOPAT to equal a historical average instead of simply last year's NOPAT. Assuming a historical average NOPAT will prove more conservative for companies that have experienced growth or improved their margins, as these companies' most recent operating profit will be higher than their historical levels. On the other hand, it benefits firms with deteriorating businesses that have experienced declines in their operating profit. Thus, this model might favor distressed value stocks (Chen & Zhang, 1998, p. 532). This will also enable the model to evaluate firms that had a negative NOPAT last year. This method would prove more effective, if the nominal EBIT or NOPAT exhibits mean reversion in the long term just as the literature argues for margins and returns on capital. Combining an average of the past operating profit with the median of past returns on invested capital also presents a more consistent approach to estimating the inputs, as both NOPAT and ROIC is measured over the same time horizon. Combining a 10Y median ROIC with last year's NOPAT, as we do in the *10Y median ROIC* might not be a realistic assumption if a firm has grown its operating profit by investing heavily, as this would have increased NOPAT at the expense of ROIC. Growth requires investments, and assuming a high recent operating profit to compound at the high historical returns on capital would be too optimistic in the previous example. In this case, the fourth model would provide a more conservative assumption to the level of NOPAT in steady state.

Backtesting the value driver models with different assumptions for growth, WACC and fundamental inputs will illustrate whether the investment performance is solid across these variations.

3.3 Investing in Morningstar’s Ratings for Stocks

Morningstar's qualitative analyst-driven equity research provides an investment recommendation expressed as a star rating, formally identified as the Morningstar Rating for Stocks. We apply several approaches to test the hypothesis that a higher star rating is associated with superior future stock returns.

At the end of every month since March 2003 we have constructed equal weighted portfolios based on the star ratings of the present stocks in the S&P 500 index. We’ve then computed the total returns in the subsequent month. To illustrate this: because Apple had a 5-star rating at the end of September 2008, we put it in a 5-star portfolio along with all other 5-star stocks and measure their return (including dividends) in October. Apple might have received the rating earlier in September, but because this paper is not an event study, we do not measure returns as of the exact date the ratings are given - unlike Bolster & Trahan (2013). If Apple maintains a 5-star rating at the end of a given month, it will be included in the equal weighted 5-star portfolio in the next month.

Both the 4-star and 5-star ratings represent undervalued stocks or, in other words, buy recommendations. Therefore, we would expect both to outperform a fair market return, while expecting higher returns from 5-star-rated stocks relative to 4-star-rated stocks. Furthermore, as the price of a 5-star-rated stock appreciates towards its intrinsic value, there is a natural movement from the 5-star rating to the 4-star rating. However, this change from 5 stars to 4 stars is not necessarily a good time to terminate the position initiated while the stock had 5 stars. 4-star stocks are still undervalued and selling stocks immediately after they have been downgraded does not give them much room to grow.

In itself, Morningstar's methodology illustrated in **Appendix 2** limits the potential upside if the stocks are only held while they have a certain rating. Going back to Apple in late September 2008 - with a price/fair value of 0.58 and a medium uncertainty, the stock cannot rise more than 21% before receiving a 4-star downgrade, if Morningstar does not increase their fair value estimate. On the other hand, there is no limit to how much a 1-star stock can grow before it leaves the 1-star category. To accommodate this, we also compute monthly returns of portfolios combining all 4- and 5-star stocks and portfolios combining the 1- and 2-star rating.

Morningstar’s raw price/fair value has not been adjusted for uncertainty as the star ratings (**Appendix 2**), so a stock trading 10% below Morningstar’s fair value estimate will be awarded 4 stars, if it has a low uncertainty, but only 3 stars, if it has a high uncertainty. However, we would expect the uncertainty rating to affect the fair value estimates indirectly – for example with higher WACC as a result of higher uncertainty.

Since the star ratings are not based solely on the price/fair value but also on the analyst's assessment of the uncertainty around the fair value estimate, we will also test the performance of Morningstar's price/fair value on a standalone basis. Investing according to the price/fair value might tell a different story than simply looking at the star ratings.

Morningstar's fair value estimates are compared monthly with the prevailing stock price resulting in a price/fair value that we obtain from Morningstar Direct. If the stock price is lower than the analyst's fair value estimate, the price/fair value ratio will be lower than one. We will compute the returns of an equal-weighted portfolio containing all stocks trading below Morningstar's fair value estimate. Additionally, by splitting the data sample into deciles of stocks ranging from high to low price/fair value we will attempt to better describe the relation between Morningstar's fair value estimates and future stock returns. All Morningstar portfolios are rebalanced and equal weighted at the end of each month.

3.4 Modelling and Performance Evaluation

When the fair values of the stocks have been estimated, we determine the ratio of price (market cap) to fair value for each stock in the S&P 500 index according to each of the valuation models described in **Section 3.1** and **Section 3.2**. All stocks with a price/fair value below one is considered undervalued. Portfolios are constructed for each valuation model that buys every undervalued stock each month. We evaluate the performance on these long-only portfolios but also construct and evaluate long/short portfolios. Finally, we form quartile and decile portfolios of the most undervalued to the most overvalued firms.

- **Universe:** Securities in the S&P 500 index excluding financials and duplicates (S&P 500 adj.) in each specific month from the start of February 2003 to the end of September 2018.
- **Signals:** Fair values are calculated at the end of each month based on past financials and compared to the market cap on the same day (end of month).
- **Trading rules:** The portfolios are rebalanced on a monthly basis and are equal weighted. We also test value-weighted portfolios of the Gordon Growth models.
- **Time lags:** The standard valuation models can trade on the same closing prices used to produce our signals, but we also test the performance of trading on 1-month old signals (1-month lag).

To determine risk-adjusted returns, the Sharpe ratio is calculated in the following way (Pedersen, 2015 p. 29):

$$Sharpe\ ratio = \frac{(R - R_f)}{\sigma(R - R_f)}$$

$(R - R_f)$: Excess return above the risk-free rate
$\sigma(R - R_f)$: Standard deviation of excess return

To determine the explanatory power of the regression we normally calculate R-squared, but in this case adjusted R-squared is more optimal because it punishes "overfitting" and thereby reduce the explanatory power if more variables are included in the regression model. The formula is the following (Bowerman, O'Connel & Koehler, 2005 p. 157):

$$Adj. R^2 = (R^2 - \frac{k}{n-1}) \times (\frac{n-1}{n-(k+1)})$$

k: Number of variables
n: Number of observations

Often returns are divided into alpha and beta. Beta (slope) is the exposure of a security to the market volatility and alpha (intercept) is the excess return after accounting for typically the market performance but also all sorts of other strategies. These are both computed by running a regression of the strategy's excess return on the market excess return (Pedersen, 2015 p. 27):

$$R_x - R_f = \alpha + \beta \times (R_m - R_f) + \epsilon$$

R_m: Market return
R_f: Risk-free rate
R_x: Return on portfolio x
ϵ: Error term (random noise)

Alpha is also calculated from the Fama & French 3-factor model, which adjusts for size and value (1993). This is done by running a multiple regression of the strategy's excess return on the returns of market, size and value, as follows (Pedersen, 2015 p. 29):

$$R_x - R_f = \alpha + \beta_m \times (R_m - R_f) + \beta_{HML} \times R_{HML} + \beta_{SMB} \times R_{SMB} + \epsilon$$

β_{HML}: Beta load on value (high minus low portfolios)
R_{HML}: Returns of high minus low portfolios
β_{SMB}: Beta load on size (small minus big portfolios)
R_{SMB}: Returns of small minus big portfolios

To determine whether a variable such as alpha is significantly different from zero, the t-statistic is calculated in the following way (Newbold, Carlson & Thorne, p. 353). If the t-statistic is above 1.96 and the sample size is above 100 then the value is significantly different from zero with 95% confidence (Newbold, Carlson & Thorne, 2013 p. 738).

$$\text{t} - \text{statistic} = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n-1}}$$

$\bar{x}$: Average of the sample
μ_0: In this case 0 since we want to test whether the hypothesis is different from 0.
σ: Standard deviation

Information ratio is calculated to determine the risk adjusted alpha. This is done by dividing alpha by the standard deviation on residuals (Pedersen, 2015 p. 30):

$$IR_x = \frac{\alpha_x}{\sigma_e}$$

α_x: Alpha on portfolio x
σ_e: Standard deviation on residuals
IR: Information ratio

Benchmarks for evaluating performance
To evaluate the performance and calculate beta and alpha for the different trading strategies we need a market benchmark to regress against. The literature on factor models typically utilize the Kenneth French market portfolio, which includes all stocks listed on the New York Stock Exchange, Nasdaq and the American Stock Exchange (French, 2018). Since our universe (the S&P 500 excluding financials and duplicates) is smaller and only contain some of the largest stocks on the U.S. market, we supplement the typical methodology by applying two additional benchmarks.

The second benchmark is the S&P 500 index total return. A simple and more relatable index to many investors. But since the S&P 500 is market-cap weighted and includes financial stocks in contrast to our universe, we might be able to create a more precise and fair benchmark. The third benchmark is the return of our data sample of stocks, so excluding financials, duplicates. We calculate the third benchmark as equal weighted. The base model for our portfolios is equal weighted while the S&P 500 and market portfolio are market-cap weighted, which also results in frictions.

4 – Backtesting Performance

In this section we will assess whether the quantitative terminal value measures described above can successfully carry out one of the most important tasks of equity analysts; provide profitable investment recommendations. To test this, we will compare the models to various benchmarks and control for several common risk factors to find out if the investment strategies are taking on more risk to achieve superior returns or if they provide true alpha (Pedersen, 2015, p. 29).

4.1 Performance of the Gordon Growth Models

This section will measure the performance of the Gordon Growth models discussed in **Section 3.1**. The following portfolios are long-only and invest only in companies that have a price/fair value below one and above zero (all stocks that have a positive valuation higher than their market cap). The portfolios are equal weighted. WACC is determined from the Morningstar sample and the growth rate is 3.95%. The results of the strategies are illustrated in **Table 4.1**.

Table 4.1: Return and risk of the long-only Gordon Growth strategies versus the benchmarks

	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.	Market	S&P 500	S&P 500 adj.
Ann. Excess return	14.54%	13.97%	12.87%	12.90%	15.50%	15.53%	17.34%	9.75%	10.33%	12.53%
Ann. volatility	14.90%	14.71%	14.29%	14.16%	15.11%	15.18%	17.08%	13.20%	13.58%	14.64%
Ann. Sharpe ratio	0.98	0.95	0.90	0.91	1.03	1.02	1.02	0.74	0.76	0.86
Cumulative return	9.49	8.73	7.44	7.50	10.95	10.97	13.87	4.72	5.11	5.85

Annualized arithmetic average, Sharpe ratio and Cumulative return for Gordon Growth strategies.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

We apply three different benchmarks as described in **Section 3.4**. The first thing we notice is that all the benchmarks have relatively high returns and Sharpe ratios in the period. The average return of the U.S. market portfolio since the Second World War has been 8% with a Sharpe ratio of 0.5 (Cochrane, 2000 p. 414). So, our 15-year period has experienced relatively high risk-adjusted returns. The benchmarks have given average annualized returns between 9.75% and 12.53% above the risk-free rate with a Sharpe ratio between 0.74 and 0.86. Our sample (the S&P 500 excluding financials adjusted for duplicates) is the strongest benchmark.

However, the Gordon Growth portfolios strongly outperform each benchmark. They have Sharpe ratios between 0.90 and 1.03 and annualized excess return between 12.87% and 17.34%. The highest Sharpe ratio is generated by the 3-year average FCFF portfolio with a Sharpe ratio of 1.03 and excess returns of 15.5%. The strategy with the highest return (17.34%) is the 10-year average FCFF. We notice that the Sharpe ratios and returns are in general higher for the strategies where we apply a historical average of FCFF instead of a normalized FCFF. Another interesting finding is that the simplest of the strategies, where we just assume the last year FCFF to grow in perpetuity is the fourth strongest of the Gordon Growth strategies.

Sector exposure

We were curious to see whether our valuation models favored some sectors over others. This analysis is based on Morningstar sectors (not Global Industry Classification Standard (GICS)), so communication services do not include recent technology additions such as Facebook, Alphabet, and Netflix. **Table 4.2** illustrates the sector exposures of the strategies relative to the total sample. This analysis is performed by calculating the total trades in a sector for a specific strategy and dividing it by the strategy's total trades. This number is compared to the sector exposure of the S&P 500 adjusted. The adjusted benchmark is equal weighted, so the sector weights are different than what you would see in the classic S&P 500 index that has larger exposures to a few large tech-names. The formula applied is illustrated below:

$$LY\ FCFF_{Tech\ exp} = \frac{Total\ trades\ in\ Tech_{LY\ FCFF}}{Total\ trades_{LY\ FCFF}} - \frac{No.of\ Tech\ stocks_{S\&P500\ adj.}}{Total\ no.of\ stocks_{S\&P500\ adj.}} = -2\%$$

Tech: technology companies

Exp: technology sector exposure

A value of -2% indicates that the portfolio (on average) includes 2% fewer technology stocks than the benchmark in the 15-year period.

Table 4.2: Relative sector exposure of the Gordon Growth strategies

	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.
Technology	-2%	-2%	-2%	-2%	-1%	0%	2%
Consumer Cyclical	0%	0%	-1%	-1%	1%	1%	4%
Healthcare	2%	1%	2%	4%	1%	2%	3%
Energy	-2%	-3%	-3%	-3%	-3%	-3%	-3%
Communication Services	0%	0%	0%	-1%	0%	-1%	-2%
Consumer Defensive	5%	7%	7%	7%	6%	6%	6%
Industrials	1%	1%	0%	0%	0%	-2%	-3%
Basic Materials	0%	0%	0%	0%	0%	0%	-1%
Utilities	-1%	-1%	-1%	-1%	-1%	-1%	-2%
Real Estate	-2%	-2%	-3%	-3%	-3%	-3%	-3%

Sector exposure for Gordons Growth strategies. The larger the green bar, the larger the overweight in a sector compared to the S&P500 adj. index and the opposite for the red bars.

Weighting: Equal weighted and monthly rebalancing
Growth: 3.95%
WACC: Morningstar sample test
Source: Morningstar direct, Kenneth French database and own estimations.
Market & period: 2003.04-2018.09, S&P 500 excluding financials and duplicates

Table 4.2 illustrates that all the Gordon Growth strategies overweight stocks in less cyclical sectors such as consumer defensive and healthcare. The strategies typically overweight consumer defensives with at least 5% and healthcare with at least 1%. If we calculate the total sector weights, the largest exposure is to consumer cyclicals - simply because this sector has taken up most space in the index during the period (**Appendix 4**).

Table 4.3 illustrates the fundamentals in the different sectors to get an understanding of why the strategies over- or underweight a sector. Each month, we calculate the average EBIT margin, revenue growth, etc. for every stock in the S&P 500 excluding financials based on the numbers of the last fiscal year with a 2-month lag. We do this for each of the 10 sectors. We then take a median of the monthly observations from 2003 to 2018 to eliminate outliers.

Table 4.3: Sector fundamentals

	Book/ Market	Sales/ Market	FCFF/ EV	EBITDA/ EV	ROIC	EBITDA-margin	EBIT-margin	NIBD/ equity	E/P	1Y revenue growth
Technology	0.32	0.36	0.04	0.07	16%	19%	12%	-0.29	0.03	7%
Consumer Cyclical	0.32	0.88	0.04	0.10	13%	14%	10%	0.46	0.05	7%
Healthcare	0.28	0.35	0.02	0.07	17%	22%	17%	0.19	0.04	6%
Energy	0.48	0.59	0.00	0.11	9%	25%	17%	0.38	0.04	7%
Communication Services	0.35	0.73	0.04	0.13	9%	30%	17%	0.75	0.06	6%
Consumer Defensive	0.25	0.61	0.03	0.09	17%	18%	14%	0.52	0.05	6%
Industrials	0.31	0.73	0.03	0.10	14%	16%	12%	0.46	0.05	7%
Basic Materials	0.40	0.81	0.03	0.11	13%	18%	12%	0.47	0.04	7%
Utilities	0.61	0.80	0.01	0.11	6%	28%	18%	1.31	0.05	8%
Real Estate	0.42	0.11	0.00	0.05	5%	63%	30%	1.13	0.03	8%

Different fundamentals on a sector level.

Source: Morningstar Direct and own estimations.
Period: 2003.04-2018.09

Table 4.3 indicates why the portfolios favor consumer defensives, as the sector has large free cash flow yields (FCFF to enterprise value). Combined with a low Morningstar WACC, stocks in this sector are set up for high valuations in the models.

The healthcare sector is overweighted across strategies during the period, but healthcare has not appeared particularly cheap during the period. We must again turn towards the low sector WACC of 7%, which is the second lowest in our Morningstar sample. With a lower WACC, valuations increase, so this can possibly explain our exposure to healthcare. This illustrates one of the benefits of using the single-period valuation model instead of relying on simple price multiples such as earnings/price and book/market that do not adjust for risk (cost of capital). The large healthcare stocks in the S&P 500 might not look cheap on multiples, but many of them have sustainable competitive advantages (moats if you ask Morningstar), and their business models are stable across market cycles - factors that contribute to lower risk and lower cost of capital.

Because our valuations apply the lower WACC of healthcare, they have increased their exposure to the best performing sector in the period. Later in this section, we will investigate how stressing our assumptions to WACC will change the sector exposures.

When we base our estimate of steady-state FCFF on a longer historical average of free cash flow, we get more exposure to consumer cyclicals and technology which have been strong performers in the 15-year period. This is interesting because the 3-, 5-, and 10-year average free cash flow portfolios all have the highest Sharpe ratios above 1. The 10Y average strategy has the highest exposure towards consumer cyclicals and the technology sector relative to the adjusted S&P 500.

Since our portfolios have materially different sector exposures compared to the index, they provide abnormal returns from both allocation and stock selection. They gain from allocation by overweighting high-return sectors such as healthcare while underweighting sectors such as energy, real estate, and utilities with lower returns. The portfolios gain from stock selection as they pick the most undervalued stocks within each sector.

The number of undervalued stocks vary over time

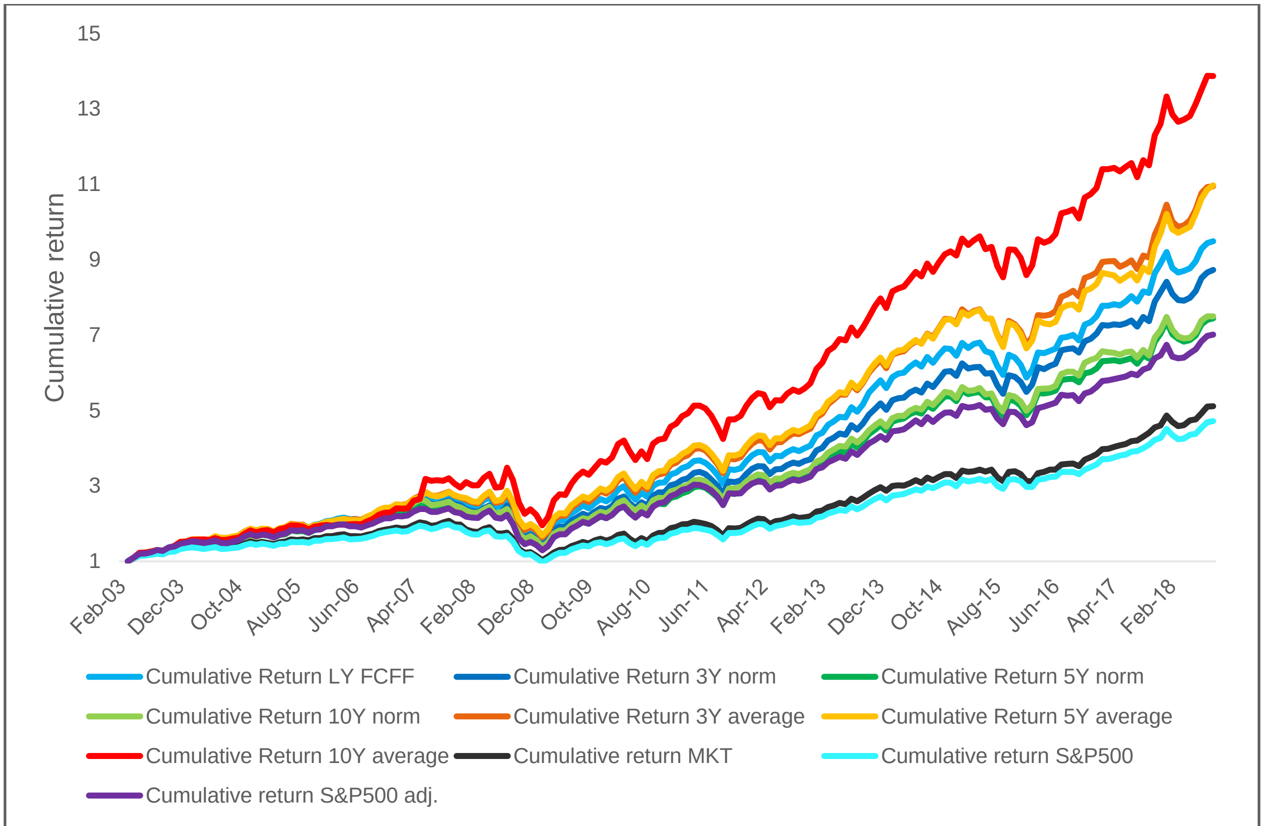
Appendix 6 illustrates the average number of stocks in our portfolios in each month from 2003 to 2018. The portfolios never find less than 30 undervalued stocks, which is enough to maintain some diversification. During the financial crisis, each of the portfolios invested in up to 250 stocks (more than half of all the stocks in the S&P 500 excluding financials). Owning too many stocks makes it more difficult to outperform the index, as the performance may easily imitate the index. It makes sense that a value strategy would find more undervalued stocks during the crisis, as prices fell dramatically while past fundamentals stayed the same.

The last year free cash flow strategy had the largest number of holdings and the 10Y average FCFF had the least. This is a natural outcome owed to how we built the valuation models in **Section 3**. It is a bit surprising that the strategy with one of the highest Sharpe ratios and returns is the one with the least trades - not only because it is less diversified with fewer holdings but also because we originally expected it to underweight growth stocks and especially the technology sector, which has performed well since 2009. However, having a more concentrated portfolio also increases the probability of outperforming, if the right stocks have been picked. The lower amount of trades benefits the 10Y average portfolio when we adjust for transaction costs later.

Cumulative returns

We have plotted the cumulative returns of the Gordon Growth strategies on **Figure 4.1** below. The cumulative returns move in the same patterns but with different magnitudes. All strategies outperform the three market benchmarks (the three lines in the bottom). The adjusted S&P 500 has consistently been the best performing benchmark throughout the period. The 10Y average portfolio has the highest cumulative return. The 10-year average have outperformed the other strategies in terms of cumulative return since 2007. After 2008 the distance between the 10Y average FCFF and the rest of the strategies becomes larger and larger.

Figure 4.1: Cumulative total returns of the Gordon Growth strategies



Cumulative return for Gordon Growth strategies.

Weighting: Equal weighted and monthly rebalancing
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Market & Period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

It is noticeable that the 10Y average FCFF materially outperforms the other strategies around the financial crisis in 2007, 2008, and 2009. On the one hand, the 10Y FCFF strategy is less diversified going into the crisis, because it has fewer holdings. On the other hand, the strategy favors stocks with stable long-term free cash flows, which intuitively should be a favorable characteristic when credit markets freeze and make it more difficult to borrow.

This makes it easier for firms with high free cash flows to meet their obligations and still invest in future growth. However, as we discover in the sections below, the 10Y FCFF model tend to invest in firms with higher leverage (NIBD/Equity), which might not be handy in a debt crisis. The 3- and 5-year average portfolios perform similarly and have also outperformed the other strategies since 2009. The lowest cumulative return was produced by the 5- and 10-year normalized strategies.

The strategies are highly correlated with correlations between 0.89 and 0.99 as seen in **Appendix 7**. The strategy which is least correlated with the other strategies is the 10-year average FCFF.

Loadings on common risk factors

Table 4.4 illustrates the factor loadings and the different performance measures for the investment strategies. The CAPM and 3-factor alphas are based on the Fama & French market portfolio and their factors for size (SMB) and value (HML).

Table 4.4: Factor loadings and performance of the Gordon Growth strategies

Simple investment strategy Gordon Growth Models	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.
Ann. Excess return	14.54%	13.97%	12.87%	12.90%	15.50%	15.53%	17.34%
CAPM alpha	4.91%	4.47%	3.61%	3.85%	5.87%	5.94%	7.61%
t-stat	4.28	3.97	3.56	3.39	4.45	4.20	3.15
3-factor alpha	5.03%	4.53%	3.70%	4.07%	6.02%	6.09%	7.89%
t-stat	4.55	4.12	3.71	3.72	4.73	4.45	3.33
MKT beta	1.00	1.00	0.98	0.96	1.00	0.99	0.99
t-stat	39.76	39.71	43.09	38.27	34.36	31.77	18.28
SMB beta	0.13	0.12	0.08	0.04	0.13	0.14	0.15
t-stat	3.16	2.82	2.19	0.91	2.73	2.68	1.69
HML beta	0.10	0.06	0.07	0.15	0.12	0.13	0.21
t-stat	2.67	1.65	2.11	3.87	2.75	2.69	2.51
Sharpe ratio	0.98	0.95	0.90	0.91	1.03	1.02	1.02
Information ratio (3-factor)	1.14	1.05	0.95	0.94	1.19	1.12	0.85
Adjusted R^2 (3-factor)	94.06%	93.88%	94.97%	93.30%	91.66%	90.15%	73.61%

Factor loadings and performance measures for the Gordon Growth simple investment strategies. The strategies is long only and invest in companies with a price to fair value below one.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Market & Period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

The annualized abnormal returns, or CAPM alphas, across our strategies are consistently high ranging from 3.61% to 7.61% in **Table 4.4**. The alphas are statistically significant at a 95% confidence level with t-values above 1.96. Harvey, Liu, and Zhu (2015) address the issue of data mining when it comes to the discovery of anomalies and advocate that factors should have a t-value above 3 to be deemed valid. The alphas identified in **Table 4.4** also pass the bar set forth by Harvey, Liu, and Zhu.

Initially, we were surprised that the 3-factor alphas are higher than the CAPM alphas. We suspect that the explanation for the higher 3-factor alphas could be either (1) the strategies are long-only whereas the SMB and HML factors are long/short, (2) we only invest in large-cap stocks, which means that our returns could be negatively correlated with Fama and French's size factor (SMB), or (3) our measure of value is very different from the HML factor. We do, however, see similar results in other papers such as Quality Minus Junk (2013, p. 6) by Pedersen, Asness and Frazzini.

The loading towards the market beta is around 1, which means that our systematic risk is equal to that of the market portfolio. Yet, the factor loadings towards both SMB and HML are low, which indicates, that our measure of value is far from the HML (which only looks at book-to-market ratios). Although we do not find a negative loading on size, our returns only have a limited correlation with SMB.

The adjusted R-squared is in general high across strategies, so the explanatory power of the multiple regression on the returns is high but does not exceed 95%. The adjusted R-squared for the 10-year average free cash flow is much lower than the other strategies on 73.6% which are all above 90%. The adjusted R-squares are comparable to the ones calculated in the Quality minus Junk study which is also above 90% (Pedersen, Frazzini, Assnes, 2015).

The highest alpha both for CAPM (7.61%) and 3-factor (7.89%) is obtained by the strategy with the highest excess return and the second highest Sharpe ratio, which is the 10-year average free cash flow. This strategy has a higher beta exposure to HML (0.21) than the other strategies, which tells us that it is more correlated with the value factor and tend to invest in cheap stocks (Pedersen, 2015, p. 29). The t-stats of the 10Y average FCFF alphas are lower than the other portfolios, which indicates more volatile abnormal returns.

Returns in different time periods

Table 4.5 shows the excess returns of the long-only Gordon Growth portfolios in each year from 2003 to 2018. In most years, the portfolios outperform their benchmarks. In 2008 where the markets experienced the largest drop due to the financial crisis, all the strategies outperformed considerably. This suggests that the single-period valuations are relatively defensive during times of market turmoil. Most of the portfolios underperformed with negative returns in 2015, where the market and S&P 500 generated small positive returns. Although some of the portfolios have outperformed the S&P 500 adjusted in 2017 and 2018, most of them have underperformed the market portfolio and the classic S&P 500.

Table 4.5: Returns of the Gordon Growth strategies over 1-year periods

Simple investment strategy - average excess return	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.	S&P 500	Market	S&P 500 adj.
2003	55.0%	49.7%	47.2%	44.2%	55.1%	56.9%	56.1%	38.0%	41.1%	52.3%
2004	18.9%	18.2%	17.1%	17.2%	20.9%	19.7%	17.8%	9.4%	10.5%	14.7%
2005	6.6%	5.6%	6.3%	9.2%	3.6%	3.6%	4.6%	2.1%	3.3%	5.1%
2006	14.2%	16.5%	14.8%	17.3%	15.8%	16.0%	12.1%	10.2%	9.9%	10.6%
2007	4.3%	2.8%	1.8%	0.5%	6.8%	6.6%	23.1%	1.2%	1.4%	1.8%
2008	-32.6%	-35.2%	-37.9%	-35.5%	-31.4%	-27.7%	-17.3%	-44.7%	-44.2%	-38.4%
2009	40.0%	37.9%	34.7%	35.6%	43.6%	42.1%	47.8%	25.9%	27.4%	40.9%
2010	23.9%	23.7%	22.0%	22.8%	23.9%	23.4%	24.1%	15.7%	17.9%	23.0%
2011	6.0%	5.5%	6.6%	5.2%	6.8%	7.4%	7.5%	3.2%	1.7%	4.3%
2012	16.6%	17.1%	16.5%	15.2%	18.9%	18.2%	17.0%	15.4%	15.7%	15.2%
2013	36.3%	34.5%	33.7%	32.3%	34.6%	33.8%	33.9%	28.7%	30.9%	29.4%
2014	13.9%	15.7%	15.9%	15.3%	16.2%	15.2%	15.0%	13.2%	11.5%	14.0%
2015	-5.7%	-4.0%	-4.0%	-3.5%	-3.6%	-4.4%	-1.0%	2.2%	0.9%	-1.6%
2016	17.3%	18.7%	16.6%	19.8%	19.5%	16.4%	17.7%	11.6%	13.1%	13.2%
2017	18.8%	16.1%	15.3%	11.4%	15.0%	16.1%	15.7%	19.2%	19.6%	15.6%
2018	7.4%	8.1%	6.3%	5.5%	11.0%	15.4%	11.6%	12.3%	12.9%	9.7%
Average return	14.5%	14.0%	12.9%	12.9%	15.5%	15.5%	17.3%	9.8%	10.3%	12.5%

Annualized arithmetic average excess returns for the different long-only Gordon Growth strategies over time. The cells are formatted green if returns are above the S&P 500 adj. return and red if below.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Market & Period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Table 4.6 zooms in on the returns during the financial crisis from December 2007 to June 2009 (NBER, 2019). The strategy that best survived the crisis was the 10Y average with an annualized return of -0.5%. This was also the most conservative strategy in terms of valuations, and consequently, it held much fewer stocks during the period (but was still fully invested). The worst strategy was the 5 year normalized strategy with an annualized return of -16.3%.

Table 4.6: Returns of the Gordon Growth strategies during the financial crisis

Crisis performance	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.
Average ann. return	-10.8%	-12.8%	-16.3%	-15.3%	-9.0%	-7.6%	-0.5%

The table illustrates the annualized return during the financial crises from December 2007 to June 2009 for the long-only Gordon Growth strategies.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Market & Period: 2007.12-2009.06, S&P 500 excluding financials an duplicates

Fundamental characteristics of undervalued stocks

Table 4.7 illustrates the fundamentals of the long-only Gordon Growth portfolios. The stocks in the portfolios of the 3-, 5-, and 10Y Average FCFF models have almost had no revenue growth in the year before they were included in the portfolio. On other fundamentals such as price multiples, margins, and leverage, all the Gordon Growth strategies appear similar somewhat. The strategy with the highest return on invested capital and the largest EBIT and EBITDA margin is the 10Y normalized FCFF. In terms of leverage the 10Y average FCFF has the highest leverage, which is not what we had expected considering its performance during the financial crisis.

Table 4.7: Fundamental characteristics of undervalued stocks in the Gordon Growth models

Fundamentals for simple investment strategy	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.
Book to market	0.49	0.49	0.49	0.50	0.52	0.53	0.58
Sales to market	1.25	1.39	1.36	1.41	1.48	1.54	1.61
FCFF/EV	8.6%	7.1%	6.7%	6.9%	8.1%	8.0%	9.4%
NIBD/EQT	0.57	0.53	0.52	0.57	0.41	0.45	0.71
Earnings to price	4.3%	4.5%	5.0%	5.6%	4.1%	4.9%	4.6%
ROIC	16.3%	17.2%	19.4%	24.3%	16.7%	15.9%	19.7%
1Y revenue growth	4.5%	5.1%	5.1%	5.3%	1.7%	1.2%	0.1%
EBIT margin	13.2%	13.3%	13.3%	15.4%	13.9%	14.2%	13.6%
EBITDA margin	19.8%	19.6%	19.4%	20.9%	20.1%	19.8%	18.6%
EBITDA/EV	11.5%	11.9%	12.3%	13.0%	12.0%	12.2%	12.5%

Average fundamentals for the different Gordon Growth strategies.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Market & Period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Decile analysis of the Gordon Growth models

In the following analysis, the stocks are divided into decile portfolios depending on their price/fair value in each valuation model. We do this to observe how the performance changes when going from low to high price/fair values.

Table 4.8 shows that across all Gordon Growth strategies, excess returns and Sharpe ratios increase going from low value (high price/fair value) portfolios to high value portfolios (low price/fair value) - or from the 10% most overvalued stocks to the 10% most undervalued stocks. As such, our valuation models can sort the best and the worst performing stocks and extract higher risk-adjusted returns by choosing portfolios including undervalued instead of overvalued stocks. The 10 decile portfolios of each valuation model can be observed in **Appendix 8**.

Table 4.8: High Minus Low decile performance of the Gordon Growth strategies

Gordon Growth strategies Decile portfolios H-L	LY FCFF H-L	3Y Norm H-L	5Y Norm H-L	10Y Norm H-L	3Y avg. H-L	5Y avg. H-L	10Y avg. H-L
Excess ann. return	**6.92%**	**5.48%**	**3.58%**	**3.55%**	**5.22%**	**7.18%**	**6.75%**
t-values	2.40	2.04	1.31	1.18	1.74	2.15	1.92
Alpha (MKT)	**4.83%**	**4.83%**	**3.80%**	**2.95%**	**3.34%**	**2.84%**	**4.94%**
t-values	1.68	1.41	1.06	1.08	0.96	1.48	0.08
Alpha (S&P 500)	**4.87%**	**3.81%**	**2.96%**	**3.28%**	**2.89%**	**4.99%**	**7.71%**
t-values	1.70	1.41	1.06	1.07	0.98	1.49	1.24
Alpha (S&P 500 adj.)	**3.97%**	**3.29%**	**2.51%**	**3.00%**	**1.71%**	**3.69%**	**2.84%**
t-values	1.40	1.22	0.90	0.97	0.59	1.12	0.83
3-factor alpha (MKT)	**5.72%**	**4.63%**	**3.81%**	**4.41%**	**3.78%**	**5.98%**	**5.22%**
t-values	2.17	1.86	1.49	1.59	1.40	1.96	1.63
3-factor alpha (S&P 500 adj.)	**5.12%**	**4.30%**	**3.47%**	**4.12%**	**2.91%**	**5.03%**	**4.19%**
t-values	1.96	1.73	1.35	1.48	1.10	1.68	1.33
Beta (MKT)	**0.20**	**0.16**	**0.06**	**0.02**	**0.23**	**0.22**	**0.23**
t-values	3.38	2.89	1.05	0.32	3.74	3.11	0.15
Beta (S&P 500)	**0.21**	**0.17**	**0.06**	**0.03**	**0.24**	**0.22**	**0.25**
t-values	3.42	2.96	1.06	0.42	3.77	3.13	3.32
Beta (S&P 500 adj.)	**0.24**	**0.17**	**0.09**	**0.04**	**0.28**	**0.28**	**0.31**
t-values	4.32	3.37	1.59	0.74	5.04	4.42	4.76
Information ratio (MKT)	**0.44**	**0.37**	**0.28**	**0.28**	**0.25**	**0.39**	**0.32**
Information ratio (S&P 500)	**0.44**	**0.37**	**0.28**	**0.28**	**0.25**	**0.39**	**0.58**
Information ratio (S&P 500 adj.)	**0.37**	**0.32**	**0.24**	**0.25**	**0.15**	**0.29**	**0.22**
Adj. R^2	**0.22**	**0.20**	**0.18**	**0.21**	**0.24**	**0.23**	**0.22**
Sharpe ratio	**0.61**	**0.52**	**0.33**	**0.30**	**0.44**	**0.55**	**0.49**

High minus low (Short low value and long high value) for different performance measures for the Gordon Growth strategies.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Alpha and beta are both calculated using the Kenneth French market return, the return of the S&P 500, and the return on the equal weighted S&P 500 adj. The CAPM alphas are increasing going from low to high value for all strategies - meaning that high price/fair value portfolios have lower abnormal returns than low price/fair value portfolios.

In **Appendix 8**, the t-values across the different strategies do not have a clear pattern, but it is positive that the high value decile portfolios have higher t-values. The excess returns and alphas are generally not significantly different from zero for the high minus low portfolios. A possible explanation for this is that the portfolios become smaller and more volatile when they are divided into deciles and therefore are less likely to become significantly different from zero.

Because the portfolios are long/short portfolios, which hedges away much of the market return, the Sharpe ratios and t-values consequently become much lower (Pedersen, 2015, p. 53). The model with the highest increase in terms of Sharpe ratio going from low to high value is based on last year free cash flow, which also has the largest alphas going from low to high.

In **Table 4.8**, the 3-factor alphas regressed up against the market, size and value factor (Fama and French, 1993) are increasing for all strategies going from low to high value, which is a positive result. From the CAPM theory (Sharpe, 1964), we expect that higher expected returns should be explained by higher beta. The deciles with higher returns do also have higher market betas, but since they still produce alpha, the higher market betas do not explain all of our abnormal returns. The higher betas indicate that undervalued stocks have higher systematic risk. According to CAPM, it should not be possible to produce alpha in efficient markets (Pedersen, 2013, p. 3). Yet, significant alphas have been found systematically in many other studies on anomalies such as Betting Against Beta (Pedersen, Asness & Frazzini, 2013), Quality Minus Junk (Pedersen, Asness & Frazzini, 2013), and Momentum (Asness, 1994).

The explanatory power (R-squared) of the 3-factor model increases for all the strategies going from low to high value, which means that the market, HML and SMB better explain the returns of undervalued stocks than overvalued stocks. This is in line with the undervalued stocks having higher beta and a positive load on the value and size factors.

Fundamental characteristics of undervalued stocks

Table 4.9 shows the price/fair value deciles in terms of how they are exposed to general value multiples such as book to market, sales to market, and free cash flow to enterprise value. We would expect to find stronger value multiples on the most undervalued stocks, because cash flow based valuations explain multiples as we clarified in **Section 2.2**. This is consistent with our results.

We find that stocks with low price/fair values also have more attractive multiples than stocks with high price/fair values. Book to market is one of the most used multiples to measure value versus growth stocks and is also used by Fama and French. We would expect the free cash flow to enterprise value to line up closely with our valuation models - especially the valuation model based on last year FCFF. We use FCFF to EV instead of FCFF/Market because FCFF is the cash flow available to serve both debt- and equity holders. An alternative is free cash flow to equity FCFE/EV.

Table 4.9: Difference in fundamentals between the high and low value decile of Gordon Growth

Fundamentals Gordon Growth strategies H-L	**LY FCFF H-L**	**3Y Norm H-L**	**5Y Norm H-L**	**10Y Norm H-L**	**3Y avg. H-L**	**5Y avg. H-L**	**10Y avg. H-L**
Book/Market	0.28	0.21	0.21	0.13	0.29	0.24	0.17
Sales/Market	1.25	1.18	1.18	0.89	1.34	1.29	1.11
FCFF/EV	16.5%	12.0%	12.0%	7.9%	12.8%	11.2%	10.6%
EBITDA/EV	5.0%	7.0%	7.0%	9.3%	5.9%	5.4%	5.3%
ROIC	-3.1%	0.7%	0.7%	9.6%	-1.8%	-3.6%	-3.0%
EBITDA margin	-10.2%	-3.8%	-3.8%	-0.2%	-5.5%	-5.9%	-5.6%
EBIT margin	-10.9%	-2.4%	-2.4%	0.5%	-4.6%	-4.6%	-3.9%
NIBD/Equity	-0.20	0.18	0.18	0.42	0.05	0.07	0.81
Earnings/Price	-2.7%	0.2%	0.2%	3.8%	-2.0%	-0.9%	-0.7%
1Y revenue growth	-11.8%	-10.4%	-10.4%	-7.0%	-18.6%	-17.2%	-15.7%

Shows the difference in fundamentals between the high and low value decile in the Gordon Growth models. Differences in percentage points.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

In terms of profitability and margins, the most undervalued stocks in most of our models have lower ROIC, EBITDA and EBIT margins than the most overvalued stocks. This indicates that more profitable companies are also more expensive. It also shows that our models might invest in stocks that are “cheap for a reason”. In terms of revenue growth, the most undervalued stocks in the valuation models based on average FCFF have considerably lower growth than their most overvalued counterparts. This also provides an indication of why they are cheap. Generally, undervalued stocks are more leveraged with higher net interest bearing debt as opposed to equity. The higher leverage can also explain why the most undervalued stocks have higher beta, as this makes them more vulnerable to changes in the economy. The full picture on a decile level for these fundamentals can be observed in **Appendix 9**.

Quartile analysis

In the following section, the seven different strategies have each been divided into four different quartile portfolios depending on their price/fair values. This can be seen on **Table 4.10** and in **Appendix 10**. We note that the results are to some extent the same as for the deciles analyzed above. We still see increasing alphas, Sharpe ratios and excess returns going from low to high value.

The benefit of dividing all stocks into quartile portfolios is that the portfolios consist of more stocks, which reduces volatility and increases the statistical significance as seen in **Appendix 10**. The t-values on the long/short high minus low portfolios are in general higher for quartile portfolios than for deciles.

Table 4.10: Gordon Growth quartile performance

Gordon Growth strategies quartile portfolios H-L	LY FCFF H-L	3Y Norm H-L	5Y Norm H-L	10Y Norm H-L	3Y avg. H-L	5Y avg. H-L	10Y avg. H-L
Excess ann. return	**6.21%**	**2.51%**	**1.14%**	**2.45%**	**7.09%**	**5.88%**	**6.16%**
t-values	2.94	1.57	0.62	1.15	3.24	2.71	2.60
Alpha (MKT)	**5.18%**	**2.02%**	**1.13%**	**2.89%**	**6.45%**	**5.21%**	**5.53%**
t-values	2.42	1.05	0.60	1.33	2.88	2.35	0.07
Alpha (S&P 500)	**5.18%**	**1.97%**	**1.04%**	**2.72%**	**6.44%**	**5.18%**	**6.84%**
t-values	2.41	1.02	0.56	1.26	2.90	2.35	2.28
Alpha (S&P 500 adj.)	**4.51%**	**1.74%**	**0.92%**	**2.81%**	**5.72%**	**4.52%**	**4.75%**
t-values	2.13	0.90	0.48	1.28	2.57	2.05	1.97
3-factor alpha (MKT)	**5.89%**	**2.72%**	**1.86%**	**3.78%**	**7.22%**	**5.98%**	**6.33%**
t-values	3.03	1.57	1.12	2.03	3.60	3.01	2.88
3-factor alpha (S&P 500 adj.)	**5.93%**	**1.86%**	**0.59%**	**2.00%**	**6.58%**	**5.22%**	**5.42%**
t-values	2.78	1.41	0.96	1.90	3.28	2.71	2.56
Beta (MKT)	**0.10**	**0.05**	**0.00**	**-0.04**	**0.06**	**0.07**	**0.06**
t-values	2.25	1.18	0.02	-0.94	1.33	1.42	1.21
Beta (S&P 500)	**0.11**	**0.06**	**0.01**	**-0.03**	**0.07**	**0.07**	**0.07**
t-values	2.30	1.36	0.25	-0.61	1.39	1.52	1.34
Beta (S&P 500 adj.)	**0.14**	**0.06**	**0.02**	**-0.03**	**0.11**	**0.11**	**0.11**
t-values	3.33	1.67	0.02	-0.69	2.57	2.56	2.44
Information ratio (MKT)	**0.63**	**0.27**	**0.16**	**0.35**	**0.75**	**0.61**	**0.60**
Information ratio (S&P 500)	**0.63**	**0.27**	**0.14**	**0.33**	**0.75**	**0.61**	**0.74**
Information ratio (S&P 500 adj.)	**0.56**	**0.24**	**0.13**	**0.34**	**0.68**	**0.54**	**0.52**
Adj. R^2	**0.21**	**0.22**	**0.25**	**0.29**	**0.22**	**0.22**	**0.20**
Sharpe ratio	**0.75**	**0.34**	**0.16**	**0.29**	**0.82**	**0.69**	**0.66**

High minus low (Short low value and long high value) for different performance measures for the Gordon Growth strategies.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

The most interesting about **Table 4.10** is that the alpha is increasing going from low to high, and several of the alphas are statistically significant. We see that the betas of the 10-year normalized strategy are actually lower for the 25% most undervalued stocks compared to the 25% most overvalued stocks.

The betas in **Appendix 10** are not rising linearly from low to high value but have a more convex shape. This means that both the most overvalued and undervalued stocks have higher market risk, whereas the stocks in the middle have lower market risk. Most of the betas of the long/short H-L quartile portfolios on **Table 4.10** are close to zero (market neutral).

We were curious to have a closer look on the 10Y Normalized FCFF model, as it exhibited decreasing beta going from the low value quartile to the high value quartile. The quartile portfolios of the 10Y Norm FCFF are illustrated in **Appendix 10**. From **Table 4.2** earlier in **Section 3.1**, we know that 10Y Norm FCFF has the highest exposure to the consumer defensive sector. This could play a part in explaining the lower betas of the most undervalued stocks, as the consumer defensive sector is generally less cyclical and has lower betas.

Stressing growth & WACC assumptions

The performance of the valuation models analyzed above are based on a steady-state growth assumption of 3.95% in line with the average GDP from 2003-2017. We have also applied 10 different sector WACC based on samples from Morningstar's equity research. In this section we will stress our assumptions to test how it will impact the performance.

We apply various steady-state growth assumptions across all our valuations on the tables in **Appendix 11**. In the tables, Sharpe ratios of the different strategies are still somewhat robust to changes in growth assumptions. The only noticeable difference is the 10-year average free cash flow, where the Sharpe ratio falls to 0.87 when the growth rate of 2.83% is applied. The best strategies are still 3- and 5-year average free cash flow in terms of Sharpe ratio.

The factor loadings do not change much with the different growth rates, but some of our long-only portfolios generate considerably higher excess returns and alpha with a slightly larger loading on the value factor (HML) when growth assumptions are lowered.

By stressing the growth rate further and applying an extreme 0% and 6% growth rate, we get the results in **Appendix 11**. Again, we find higher alphas with lower growth assumptions but more volatile returns due to fewer undervalued stocks. With zero growth, however, the sector exposures in technology and consumer cyclicals become quite extreme. Larger growth will increase the fair value of stocks with positive free cash flows and result in more undervalued stocks that could dilute our returns. But even with 6% growth, we do not find a direct relationship between higher growth and lower Sharpe ratios. It seems that, the more conservative we make our steady-state assumptions, the better our models perform, but the trade-off is higher risk.

In **Appendix 4** and **Appendix 5**, we stress our WACC assumptions and illustrate the sector distributions and performance. We see that sector distribution is highly affected by which WACC measures we use. We notice that one of our previous sector favorites, healthcare, does not look so attractively priced when we do not apply the sample WACC from Morningstar. According to Bloomberg's consensus, healthcare has the second largest WACC - and it is the fourth largest according to Damodaran. In **Appendix 4** we can observe that we get an even higher exposure to consumer cyclicals due to the relatively lower WACC.

If we observe the performance when stressing the different WACC measures, we on average get the highest Sharpe ratios when applying our sample of Morningstar's WACC estimates and the lowest with the Damodaran (NYU) WACC. This is primarily because Damodaran's WACC estimates are considerably higher which reduces our valuations and limits the amount of undervalued investments. With fewer investments, our portfolios become less diversified and more volatile. The 10Y average FCFF produces a considerably lower Sharpe ratio, as it was already the most conservative valuation model with the fewest stock holdings.

In **Appendix 4** and **Appendix 5** we have also stressed the performance by applying a constant cost of capital of 9% on all sectors. 9% is the average of all the sector WACC estimates from Bloomberg, Damodaran (NYU), and Morningstar. The performance compared to the other WACC measures is not much different, only slightly lower on Sharpe ratio. In terms of sector exposure, we are more exposed to technology and consumer cyclicals than with Morningstar's WACC.

Lagged returns

Previous Gordon Growth portfolios have been allowed to evaluate price/fair value based on the market cap at the end of each month and buy stocks at the closing price of the same month. If we stress the performance by trading on price/fair value estimates that are always one month old, we get the results in **Table 4.11**.

Table 4.11: Gordon Growth performance based on 1-month old signals

Simple investment strategy One month lag	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.
Excess return	13.90%	13.16%	12.36%	12.48%	14.74%	14.53%	15.99%
CAPM alpha	5.61%	5.05%	4.43%	4.71%	6.44%	6.12%	7.54%
t-stat	4.39	4.25	3.88	3.76	4.59	4.15	3.21
3-factor alpha	5.76%	5.16%	4.56%	4.93%	6.61%	6.31%	7.77%
t-stat	4.66	4.42	4.08	4.13	4.89	4.42	3.37
MKT beta	0.98	0.97	0.95	0.94	0.97	0.99	0.98
t-stat	34.38	36.08	37.11	34.15	31.29	30.06	18.41
SMB beta	0.10	0.06	0.04	-0.01	0.10	0.09	0.12
t-stat	2.08	1.40	0.97	-0.16	2.00	1.63	1.44
HML beta	0.14	0.10	0.11	0.19	0.16	0.17	0.21
t-stat	3.29	2.53	2.98	4.55	3.42	3.44	2.65
Sharpe ratio	0.94	0.91	0.88	0.89	0.99	0.96	0.95
Information ratio (3-factor)	1.17	1.13	1.04	1.02	1.22	1.11	0.86
Adjusted R^2 (3-factor)	91.66%	92.26%	92.72%	91.28%	89.85%	88,90%	73.80%

Performance measures and sector loadings for Gordon growth strategies based on 1-month old price/fair value signals.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Sharpe ratios are in general lower with the 1-month lag, but they are still higher than the benchmark. With a lag, the portfolios will miss out on one whole month before buying a stock that looks undervalued, which explains the lower performance. The general picture is that there is not a major impact to our performance results when we trade on 1-month old signals. The long/short results do not differ much either (see **Appendix 12**).

Long/short Gordon Growth portfolios

Most hedge funds are both long and short to hedge the market risk (beta). In fact, we have already analyzed long/short strategies for the top and bottom deciles and quartiles. It is the general practice in most papers on risk factors to analyze portfolios that buy the 30% highest decile stocks while short selling the 30% lowest decile stocks. The Fama & French value factor (HML) buys the 30% of stocks with highest book/market and short sells the 30% with lowest book/market. Similarly, we will take a deeper dive into the performance when buying the 30% of stocks with lowest price/fair value and short sell the 30% with highest price/fair values. The performance of these long/short portfolios can be seen in **Table 4.12**.

The Sharpe ratios of our long/short portfolios are naturally much lower than the long-only strategies since we hedge away the market return, which we can observe by the betas close to zero. This also affects the significance of our alphas, as only LY FCFF and 3Y Average FCFF have consistently significant alphas at a 95% confidence interval.

Table 4.12: Performance of long/short Gordon Growth strategies

Gordon growth strategies Long/short	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.
Excess ann. return	**4.42%**	**3.44%**	**2.14%**	**2.18%**	**5.41%**	**2.71%**	**3.45%**
t-values	32.97	21.80	15.46	13.97	36.40	19.08	23.38
Alpha (MKT)	**3.63%**	**3.03%**	**2.42%**	**2.88%**	**4.74%**	**2.33%**	**2.88%**
t-values	2.23	1.56	1.42	1.51	2.61	1.33	1.59
Alpha (S&P 500)	**3.63%**	**2.98%**	**2.32%**	**2.72%**	**4.72%**	**2.28%**	**2.85%**
t-values	2.23	1.54	1.36	1.42	2.61	1.31	1.58
Alpha (S&P 500 adj.)	**3.26%**	**2.62%**	**2.27%**	**2.88%**	**4.26%**	**2.02%**	**2.42%**
t-values	2.01	1.35	1.33	1.50	2.36	1.16	1.34
3-factor alpha (MKT)	**4.25%**	**3.68%**	**3.06%**	**3.66%**	**5.42%**	**3.00%**	**3.54%**
t-values	2.97	2.08	2.04	2.23	3.37	1.96	2.20
3-factor alpha (S&P 500 adj.)	**3.96%**	**3.31%**	**2.83%**	**3.50%**	**4.98%**	**2.70%**	**3.13%**
t-values	2.79	1.87	1.87	2.12	3.11	1.77	1.95
Beta (MKT)	**0.08**	**0.04**	**-0.03**	**-0.07**	**0.06**	**0.04**	**0.06**
t-values	2.26	0.99	-0.76	-1.70	1.70	1.01	1.46
Beta (S&P 500)	**0.08**	**0.05**	**-0.02**	**-0.05**	**0.07**	**0.04**	**0.06**
t-values	2.33	1.13	-0.50	-1.33	1.80	1.17	1.61
Beta (S&P 500 adj.)	**0.09**	**0.07**	**-0.01**	**-0.06**	**0.09**	**0.05**	**0.08**
t-values	2.95	1.76	-0.32	-1.51	2.63	1.63	2.38
Information ratio (MKT)	**0.58**	**0.41**	**0.37**	**0.39**	**0.68**	**0.35**	**0.42**
Information ratio (S&P 500)	**0.58**	**0.41**	**0.37**	**0.39**	**0.68**	**0.35**	**0.42**
Information ratio (S&P 500 adj.)	**0.53**	**0.35**	**0.35**	**0.39**	**0.62**	**0.30**	**0.35**
Adj. R^2	**0.27**	**0.19**	**0.24**	**0.29**	**0.24**	**0.25**	**0.23**
Sharpe ratio	**0.70**	**0.46**	**0.33**	**0.30**	**0.77**	**0.40**	**0.49**

Different performance measures for long/short Gordon growth strategies. The strategies go long the 30% with the lowest price to fair value and short the 30% with the highest prices to fair value. The Z-values are red when the test is not significantly different from zero and the t-value is therefore below absolute 1.96 for above 100 observations.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

The factor loadings of the long/short strategies are stated in **Table 4.13** below. The loading on the Small Minus Big size factor is negative, which is intuitive because all stocks in the S&P 500 are relatively large. The SMB portfolio buys small stocks and short sells large stocks, whereas our portfolios are both long and short in large stocks. When large stocks perform better than small stocks, our portfolios will outperform the market, whereas SMB will underperform. The loading on the HML value factor is materially higher than our long-only portfolios, since our long/short approach is closer to the one applied by Fama and French.

Table 4.13: Factor loadings of the long/short Gordon Growth strategies

Long/Short Gordon growth strategy	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.
Excess return	4.42%	3.44%	2.14%	2.18%	5.41%	2.71%	3.45%
CAPM alpha	3.63%	3.03%	2.42%	2.88%	4.74%	2.33%	2.88%
t-stat	2.23	1.56	1.42	1.51	2.61	1.33	1.59
3-factor alpha	4.25%	3.68%	3.06%	3.66%	5.42%	3.00%	3.54%
t-stat	2.97	2.08	2.04	2.23	3.37	1.96	2.20
MKT beta	0.02	-0.01	-0.06	-0.10	0.01	-0.01	0.00
t-stat	0.72	-0.35	-1.76	-2.56	0.25	-0.33	-0.09
SMB beta	-0.04	-0.05	-0.13	-0.21	-0.05	-0.08	-0.03
t-stat	-0.73	-0.71	-2.30	-3.36	-0.90	-1.40	-0.52
HML beta	0.37	0.39	0.37	0.43	0.40	0.39	0.40
t-stat	7.57	6.39	7.09	7.70	7.27	7.50	7.15
Sharpe ratio	0.70	0.46	0.33	0.30	0.77	0.40	0.49
Information ratio (3-factor)	0.68	0.49	0.47	0.50	0.78	0.45	0.51
Adjusted R^2 (3-factor)	26.66%	19.26%	23.79%	29.20%	24.37%	24.98%	23.34%

Different performance measures for long short Gordon growth strategies.
The strategies go long the 30% with the lowest price to fair value and short the 30% with the highest prices to fair value.

The Z-values are red when the test is not significantly different from zero and the t-value is therefore below absolute 1.96 for above 100 observations.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

The sector exposures of the long/short strategies are illustrated in **Table 4.14** below. The portfolios are consistently more long than short in consumer defensive and more short than long in technology and industrials. For example, the 10Y Normalized FCFF portfolio buys 8 more stocks in the consumer defensive sector than it goes short on an average month. **Table 4.14** also illustrates another interesting dynamic. While our long-only portfolios were generally underexposed in utilities and communication services, our long/short portfolios have net long positions in both sectors. This means that the Gordon Growth valuations might not have found many undervalued utility- and communication-stocks, but they found even fewer stocks in these sectors that were overvalued enough to short sell.

Table 4.14: Sector exposure of long/short Gordon Growth strategies

	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.
Technology	-6	-6	-7	-7	-6	-4	-0
Consumer Cyclical	-2	-1	-1	-2	0	2	2
Healthcare	4	2	4	5	1	3	3
Energy	-1	-2	-3	-2	-0	-2	-2
Communication Services	2	3	2	2	2	1	0
Consumer Defensive	6	8	9	8	6	7	5
Industrials	-5	-5	-6	-3	-5	-6	-6
Basic Materials	-1	-1	-1	-2	-1	-0	-2
Utilities	4	3	3	2	3	2	-0
Real Estate	-1	-1	-1	-1	-0	-1	-1

The difference between the exposure to long and short portfolios (Long minus short) for the different sectors for Gordons growth strategies.

Weighting: Equal weighted and monthly rebalancing
Growth: 3.95%
WACC: Morningstar sample test
Source: Morningstar direct, Kenneth French database and own estimations.
Market & period: 2003.04-2018.09, S&P 500 excluding financials and duplicates

Value-weighted Gordon Growth

In a wide range of other research papers, stocks are weighted according to their market cap - not equal weighted as in our study. This is called cap- or value-weighting and increases exposure to the largest stocks in the portfolio while decreasing the weight of the smallest stocks. Value-weighting stocks mitigates the risk of overweighting small illiquid stocks that may be very volatile and affect the performance of studies in a wider sample of stocks (such as the whole U.S. market). Another point is that there are many more small companies than large companies in the U.S., so an equal weighting will naturally overweight small caps. This risk is not as relevant in this study because the S&P 500 is a large-cap index. **Table 4.15** below illustrates the performance of value-weighted long-only portfolios based on the Gordon Growth valuations.

Table 4.15: Cap-weighting the long-only Gordon Growth strategies

Value weighting **Simple investment strategy**	**LY FCFF**	**3Y Norm**	**5Y Norm**	**10Y Norm**	**3Y avg.**	**5Y avg.**	**10Y avg.**
Ann. excess return	14.63%	14.36%	13.91%	13.67%	14.89%	14.92%	16.04%
Alpha (MKT)	6.15%	6.23%	5.86%	5.93%	6.65%	6.73%	7.98%
t-stat	5.91	5.48	4.90	4.21	5.61	4.78	4.93
3-factor alpha	6.12%	6.24%	5.91%	6.05%	6.71%	6.82%	8.14%
t-stat	6.30	5.95	5.33	4.76	6.27	5.09	5.32
MKT beta	0.87	0.84	0.83	0.82	0.86	0.84	0.83
t-stat	39.17	35.11	32.90	28.10	35.00	27.42	23.83
SMB beta	-0.19	-0.23	-0.24	-0.32	-0.27	-0.23	-0.28
t-stat	-5.07	-5.73	-5.72	-6.72	-6.61	-4.60	-4.89
HML beta	-0.06	-0.05	-0.03	0.00	-0.02	0.00	0.04
t-stat	-1.78	-1.26	-0.68	0.04	-0.50	0.08	0.71
Sharpe ratio	1.23	1.24	1.21	1.19	1.27	1.24	1.31
Information ratio (3-factor)	1.53	1.43	1.29	1.12	1.48	1.26	1.31
Adjusted R^2 (3-factor)	92.24%	89.97%	88.54%	84.20%	89.91%	83.82%	79.22%

Value weighted portfolios performance measures for Gordon growth strategies.

Weighting: Value weighted and monthly rebalancing
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

If we observe the value-weighted performance measures above, there is a few things which is interesting. Firstly, the Sharpe ratios are higher than the equal-weighted strategies. Secondly, market betas are considerably lower. We would have expected the opposite, since the Fama & French market portfolio is also value-weighted. However, the value-weighted portfolios also have significantly larger negative loadings on the size factor (SMB), which makes perfect sense as we overweight larger stocks. The best performing strategies are still the ones based on average FCFF, and the 10Y Average FCFF now has a surprisingly large Sharpe ratio of 1.31.

Table 4.16 states the performance of value-weighted long/short. The results are completely different than in the equal-weighted long/short portfolios, and excess returns are now negative for most of the portfolios although some smaller insignificant alphas remain. When the value-weighted long-only portfolios had strong performance above, the only explanation is that the cap-weighted short positions perform terribly. The value-weighted portfolios are still long and short in the same stocks as before, but the same stocks are weighted differently. It could be that the largest of the overvalued stocks have performed extremely well, which punishes us for shorting them. The FAANG stocks immediately springs to mind (Facebook, Amazon, Apple, Netflix, and Google).

Table 4.16: Value-weighting the long/short Gordon Growth strategies

Value-weighted Gordon Growth Long/short	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.
Excess return	2.89%	-0.59%	-1.37%	-2.81%	0.77%	-1.82%	-0.80%
Alpha (MKT)	3.22%	1.42%	0.61%	-0.08%	2.39%	-0.08%	0.90%
t-stat	1.66	0.65	0.27	-0.04	1.17	-0.04	0.42
3-factor alpha	3.55%	1.95%	1.24%	0.52%	3.07%	0.59%	1.54%
t-stat	1.86	0.94	0.58	0.25	1.65	0.29	0.77
MKT beta	-0.04	-0.20	-0.21	-0.25	-0.19	-0.19	-0.17
t-stat	-0.83	-4.28	-4.28	-5.10	-4.37	-4.05	-3.80
SMB beta	-0.12	-0.19	-0.19	-0.32	-0.16	-0.19	-0.23
t-stat	-1.67	-2.42	-2.38	-4.06	-2.35	-2.39	-3.06
HML beta	0.17	0.29	0.35	0.30	0.39	0.38	0.34
t-stat	2.66	4.04	4.70	4.12	6.02	5.28	5.00
Sharpe ratio	0.39	-0.07	-0.15	-0.30	0.09	-0.21	-0.09
Information ratio (3-factor)	0.48	0.23	0.14	0.06	0.39	0.07	0.19
Adjusted R^2 (3-factor)	5.44%	19.13%	20.50%	27.95%	24.43%	21.36%	21.69%

Value weighted long short portfolios performance measures for Gordon growth strategies.

Weighting: Value weighted and monthly rebalancing
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Adjusting performance for transaction costs

Several empirical asset pricing studies focus on expected gross returns without taking transaction costs into account. For practical use, transaction costs are a critical input for determining whether investment strategies are robust, implementable, and sizeable. Transaction costs might not be particularly relevant in our study, because we only trade in a universe of large and mostly liquid stocks where transaction costs are very limited. Nonetheless, we will perform an analysis of the turnover and transaction costs of the long-only Gordon Growth portfolios. According to the literature, strategies based on size, value, and momentum can be deployed at very high asset sizes and still outperform after trading costs. The return premia associated with size, value, and momentum appears to be robust, sizeable and implementable (Frazzini, Israel and Moskowitz, 2012).

Because buying and selling large volumes of shares incur transaction costs and may impact the stock prices on the market, we need to adjust our strategies to reflect this. **Section 2.4** clarified how to adjust for transaction costs and which costs that would be relevant in this thesis. We apply the median transaction cost of 4.9 bps for U.S. stocks in accordance with Frazzini, Israel and Moskowitz (2012). If we assume to liquidate our whole portfolio each month and subsequently buy all the undervalued stocks in equal proportions, then we incur 4.9 bps for selling and 4.9 bps for buying – every month. This assumption, however, incurs much higher transaction costs than if we were to just buy and sell the number of shares necessary to rebalance to an equal weighted portfolio. Since trading costs primarily depend on the size of trades and by assuming there is no minimum cost per trade, we may calculate the return after trading costs by simply deducting 9.8 bps from the portfolio returns each month. This would amount to trading costs of 1.176% per year (9.8 bps × 12). We also deduct the trading costs from the return in the last month (September 2018), because we assume to liquidate the portfolios and sell all stocks at the end of the period.

Table 4.17: Adjusting the long-only Gordon Growth strategies for transaction costs

Simple investment strategy After transaction cost	**LY FCFF**	**3Y Norm**	**5Y Norm**	**10Y Norm**	**3Y avg.**	**5Y avg.**	**10Y avg.**
Excess return	13.36%	13.38%	12.28%	12.31%	14.91%	14.94%	16.75%
Alpha (MKT)	2.53%	2.68%	1.82%	2.06%	4.08%	4.14%	5.82%
t-stat	2.22	2.40	1.81	1.83	3.12	2.96	2.43
3-factor alpha	2.64%	2.74%	1.90%	2.28%	4.22%	4.30%	6.10%
t-stat	2.42	2.51	1.93	2.10	3.34	3.17	2.59
MKT beta	1.01	1.00	0.98	0.96	1.00	1.00	0.99
t-stat	40.25	40.18	43.61	38.77	34.70	32.13	18.45
SMB beta	0.13	0.12	0.08	0.04	0.13	0.14	0.15
t-stat	3.23	2.88	2.25	0.96	2.78	2.74	1.72
HML beta	0.10	0.06	0.07	0.14	0.12	0.12	0.20
t-stat	2.62	1.59	2.05	3.83	2.70	2.65	2.49
Sharpe ratio	0.90	0.91	0.86	0.87	0.99	0.98	0.98
Information ratio (3-factor)	0.61	0.64	0.49	0.53	0.84	0.80	0.66
Adjusted R^2 (3-factor)	94.24%	94.06%	95.13%	93.50%	91.83%	90.38%	73.98%

Factor loadings illustrated for Gordon growth strategies adjusted for transaction cost. The t-stat are red when they are not significantly different from 0 with 95% confidence. Portfolios are assumed to be liquidated at the end of each month.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

As seen on **Table 4.17**, the long-only Gordon Growth portfolios maintain their abnormal returns after transaction costs, although four of the portfolios now produce annualized alphas below 3%.

When deducting transaction costs each time shares are bought and sold, then naturally the performance of strategies with high trading frequencies would suffer a larger impact. The highest measure of transaction costs is the one we have applied above, as we assume to liquidate the whole portfolio every month. If a portfolio's Apple shares have experienced high returns while its Microsoft shares have fallen in a given month, then the portfolio will rebalance the positions back to equally weighted at the end of the month by reducing the position in Apple and increasing the position in Microsoft. If a company has gone from being undervalued to being overvalued, the portfolio will not just rebalance the weight but will eliminate its position in the company. Eliminating positions or adding new shares to the portfolio typically implies selling a larger volume than if the position only has to be rebalanced, and these transactions are particularly frequent at the end of February each year, because our valuation models receive updated accounting information from the newest annual reports (10-K statements).

Table 4.18 provides a more accurate view of the portfolio turnover ratios and transaction costs. The table illustrates the annualized turnover ratio measured as the total volume bought and sold as a percentage of the total assets (let us assume this to be a constant USD 1.00 throughout the period). It also illustrates the average monthly amount of new stocks added to the portfolio and the amount of stocks removed from the portfolio. This amount divided by the average monthly portfolio size measures how many of the stocks that change on a monthly basis, on average.

The annualized turnover ratios of the Gordon Growth portfolios are very similar and range from 214% (3Y Normalized FCFF) to 251% (10Y Average FCFF). This means that the 10Y Average FCFF in an average year buys and sells stocks for an amount of USD 2.51, if we assume that the average portfolio size is USD 1.00. This suggests that the portfolios do a large amount of trading and has a fast-paced investment style (Reichart, 2009). It surprises that the models based on 10-year historical numbers have the highest turnovers, as we would assume these models to have more stable valuations. However, it makes sense that last year's FCFF has higher turnover, as the free cash flows from one year to the next can fluctuate considerably.

Table 4.18: Measuring the accurate turnover ratio and transaction costs of Gordon Growth

	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y Avg.	5Y Avg.	10Y Avg.
Annualized turnover ratio	226.81%	214.23%	213.65%	230.92%	215.56%	225.85%	251.47%
Annualized transaction costs	0.11%	0.10%	0.10%	0.11%	0.11%	0.11%	0.12%
Avg. monthly stocks sold and bought	22.05	17.59	15.84	13.27	15.68	13.19	8.92
Average monthly portfolio size	170.15	153.20	142.45	109.41	136.71	111.09	68.75
Monthly stocks sold and bought (%)	12.96%	11.48%	11.12%	12.12%	11.47%	11.87%	12.98%

Turnover ratios and transaction costs calculated for the long-only Gordon Growth strategies.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

In an average month, the LY FCFF adds 11 new stocks and removes 11 old stocks from its portfolio (22 in total), which corresponds to changing 12.96% of the portfolio. In practical terms, that means the strategies change roughly 1 in 10 of their holdings per month and leaves the other 90% of the portfolios intact. As mentioned previously, the 10Y average FCFF portfolio has the lowest amount of trades and smallest portfolio size, but it also changes the stocks in its portfolio a little more often, which results in changing 13% of its holdings each month on average.

The annualized transactions costs, calculated as 4.9 bps multiplied by the annualized turnovers amount to little more than 0.10% for all the portfolios, which is considerably lower than the 1.176% per year if we assumed to liquidate the portfolios every month. With this precise measure of our transaction costs, we can conclude that the strong abnormal performance of the long-only Gordon Growth portfolios is only affected marginally.

4.2 Performance of the Value Driver Models

The following section presents and examines how the terminal value models based on McKinsey's value driver formula would have performed as investment strategies in a 15-year backtest from April 2003 to September 2018. The section examines both long-only, long/short and decile portfolios constructed monthly by comparing our models' fair value estimates to the prevailing stock prices.

Table 4.19 illustrates that the long-only value driver strategies have generated annualized average (arithmetic) returns above the risk-free rate between 12.4% to almost 18% in the 15-year period. The lowest returning strategy applies a 10-year median ROIC in the value driver model combined with last year's NOPAT, whereas the highest returning strategy combines a 10-year average NOPAT with the 10-year median ROIC. The latter assumes that both relative profitability and absolute operating profit mean reverts to historical levels. All strategies beat the S&P 500's 9.75% return and the Kenneth French market's 10.3%. However, the portfolios have an edge over these two benchmarks due to excluding financials and being equal weighted. When we give the S&P 500 the same edge, it performs better with an excess return of 12.53% - but still lower than any of our portfolios.

Table 4.19: Return and risk of the long-only value driver strategies versus the benchmarks

	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT	Market	S&P 500	S&P 500 adj.
Ann. excess return	13.52%	14.44%	13.39%	13.45%	12.57%	14.08%	15.00%	17.57%	10.33%	9.75%	12.53%
Ann. volatility	14.36%	17.95%	14.45%	14.35%	14.14%	14.99%	15.66%	17.03%	13.58%	13.20%	14.64%
Sharpe ratio	0.94	0.80	0.93	0.94	0.89	0.94	0.96	1.03	0.76	0.74	0.86
Cumulative return	8.21	8.64	8.04	8.14	7.14	8.82	10.01	14.39	5.11	4.72	7.01

Illustrates the annualized figures of the monthly arithmetic average returns in excess of the risk free rate, standard deviation (volatility), Sharpe ratio, and cumulative returns for three benchmarks and the long-only portfolios of stocks trading below fair value based on the value driver models. The Market benchmark is from the Kenneth French database, S&P 500 is the standard cap-weighted index, and S&P adj. is an equal weighted portfolio of all the stocks included in our investable universe each month which excludes duplicates and financials.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

The most profitable portfolio managed to multiply the initial investment 14 times in the 15-year period, but this could simply be a result from data mining, since the other strategies have cumulative returns between 700% and 1,013%. Still, these results make the otherwise impressive gains of the benchmarks look muted. Although the level of volatility in the portfolios have also been elevated, which is consistent with previous research of value strategies (Pedersen et al., 2017, p. 26).

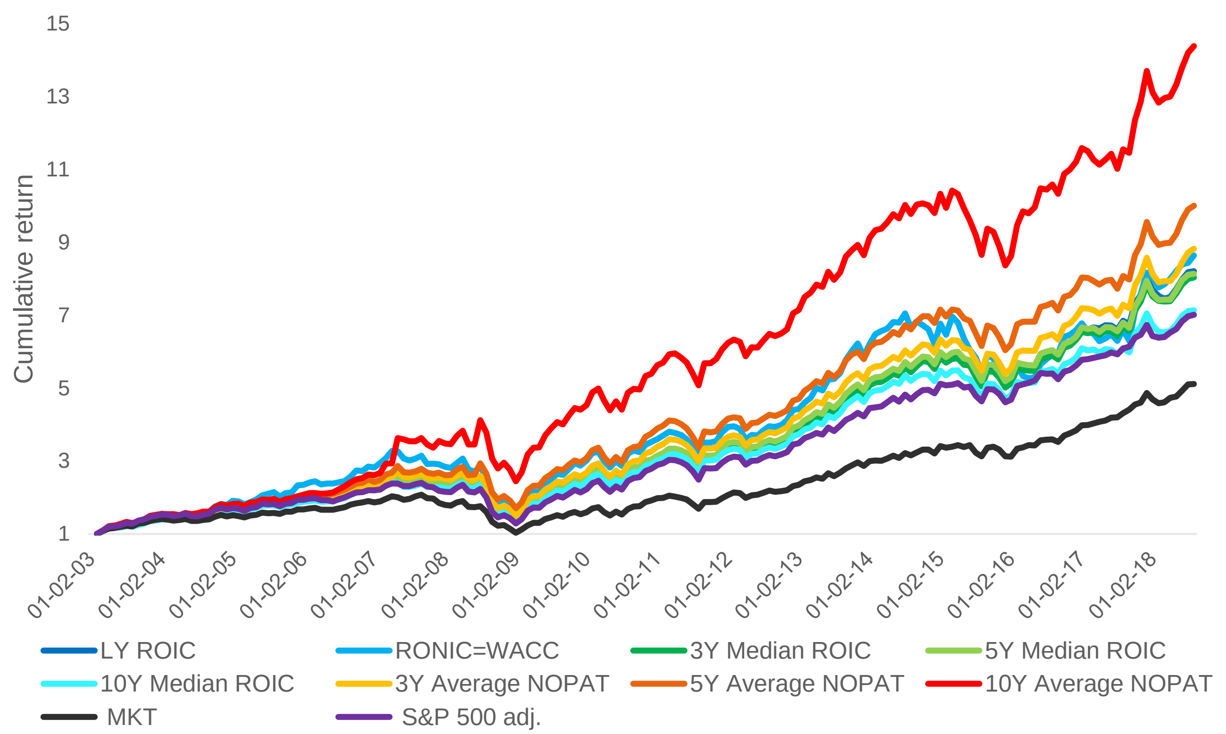
Despite higher volatilities, Sharpe ratios remain attractive at around 0.9. To put this in perspective, these Sharpe ratios compare with Berkshire Hathaway's 0.79 (Pedersen, Frazzini & Kabiller, 2018) and the S&P 500 Pure Value Index of 0.67 (from April 2003 to September 2018). Pedersen, Asness & Moskowitz (2013, p. 940) found a Sharpe ratio of 0.83 for their long-only U.S. value strategy between 1972 and 2011. One thing to note is that this is not a completely fair apples to apples comparison, since our tests have been carried out in a relatively attractive time period for the stock market. The three value driver models based on average historical NOPAT stick out as the most attractive on both returns and Sharpe ratio - an indication that assuming operating profit to mean revert is a powerful driver of returns. The Sharpe ratio of the RONIC = WACC portfolio (0.80) appear weaker compared to the other value driver models and is lower than the S&P 500 adj. (0.86).

Cumulative and annualized returns

Figure 4.2 illustrates the cumulative returns of the long-only value driver strategies. Overall, the strategies consistently beat their benchmarks over time, and since 2005, none of the strategies' cumulative returns have dived below those of the Kenneth French market or the S&P 500 adj.

The RONIC=WACC portfolio were one of the top performers until the financial crisis but the portfolio quickly recovered and had a good run until the end of 2014, where an oil-price shock loomed in the horizon. In both events the strategy experienced larger drawdowns, which eliminated its advantage over the other portfolios. This is also reflected in the high volatility of the RONIC=WACC strategy. This valuation model assumes the steady-state RONIC to equal a common sector WACC instead of applying each individual firm's own historical returns on invested capital, and this should favor the underdogs in each sector that, historically, have not been able to produce a high ROIC. With this in mind, the results can indicate that betting on undervalued companies to reach the same profitability as their peers is an outperforming strategy in up-markets but risky during market turbulence.

Figure 4.2: Cumulative returns of the value driver strategies from 2003 to 2018



Cumulative returns of the long-only value driver strategies and three benchmarks.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

The portfolios outperform the S&P 500 adj. in most years of the 15-year period, but they also experience periods of underperformance as seen in **Table 4.20**. In 2010 and 2015, all the value driver portfolios consistently underperformed. Several of the portfolios also underperform in 2009, 2012, and 2014, and as a result, if you had invested in any of the portfolios in the beginning of 2009 and sold at the end of 2015 six years later, you would have underperformed the S&P 500 adj. Instead, the models harvest much of their abnormal returns in the period between 2004 to 2008 and from 2016 to 2018. It is difficult to conclude whether the value driver portfolios are relatively robust during market turbulence, as most of them experienced much lower drawdowns in 2008 but saw losses between 5% and 14% in 2015.

Table 4.20: One-year returns of the value driver strategies

	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT	Market	S&P 500	S&P 500 adj.
2003	43.0%	50.0%	42.8%	42.7%	40.9%	46.9%	53.0%	54.8%	41.1%	38.0%	52.3%
2004	19.4%	22.6%	20.5%	20.4%	16.8%	18.1%	16.8%	18.5%	10.5%	9.4%	14.7%
2005	9.6%	14.2%	9.1%	10.2%	8.4%	7.0%	7.6%	6.4%	3.3%	2.1%	5.1%
2006	13.4%	20.2%	13.2%	11.9%	12.8%	13.8%	16.8%	20.2%	9.9%	10.2%	10.6%
2007	4.4%	3.8%	3.4%	2.8%	2.5%	7.6%	5.8%	27.1%	1.4%	1.2%	1.8%
2008	-34.9%	-41.3%	-35.4%	-32.2%	-31.1%	-32.8%	-22.9%	-9.2%	-44.2%	-44.7%	-38.4%
2009	38.9%	50.1%	40.2%	40.3%	39.6%	42.6%	42.4%	45.2%	27.4%	25.9%	40.9%
2010	20.0%	17.7%	19.5%	19.7%	20.6%	21.5%	21.3%	19.7%	17.9%	15.7%	23.0%
2011	6.1%	4.2%	6.4%	6.5%	7.0%	6.2%	5.5%	9.6%	1.7%	3.2%	4.3%
2012	15.8%	15.8%	14.9%	15.7%	13.8%	15.9%	14.8%	13.8%	15.7%	15.4%	15.2%
2013	35.3%	42.3%	34.4%	33.5%	32.7%	32.8%	31.9%	30.8%	30.9%	28.7%	29.4%
2014	14.7%	6.7%	14.6%	14.0%	12.3%	13.7%	15.5%	11.9%	11.5%	13.2%	14.0%
2015	-7.4%	-16.0%	-7.0%	-5.7%	-7.5%	-6.9%	-7.4%	-10.7%	0.9%	2.2%	-1.6%
2016	16.0%	17.1%	16.0%	14.3%	15.1%	17.8%	17.2%	22.1%	13.1%	11.6%	13.2%
2017	18.8%	16.6%	17.8%	17.7%	15.4%	17.8%	16.9%	15.5%	19.6%	19.2%	15.6%
2018	9.8%	16.4%	10.3%	9.8%	7.7%	10.5%	13.9%	14.0%	12.9%	12.3%	9.7%
Average	13.5%	14.4%	13.4%	13.5%	12.6%	14.1%	15.0%	17.6%	10.3%	9.8%	12.5%

Arithmetic average annualized excess returns of the long-only value driver portfolios and three benchmarks for each year from 2003 to 2018. Returns marked in red are lower than the S&P 500 adj. while returns marked in green are higher.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Performance-wise, our results conclude that investing in stocks trading below their terminal value in the S&P 500 has delivered attractive returns with higher, but manageable, volatility in the past 15 years. But can these abnormal returns be explained by higher exposure to common risk factors? This will be evaluated below.

Factor loadings

Table 4.21 regresses the long-only value driver portfolios on standard risk factors. We find substantial and statistically significant annualized abnormal returns (alpha) between 3.6% and 8.7% across most of the portfolios. The value driver models based on 3-, 5-, and 10-year average NOPAT have the highest alphas, while the RONIC=WACC portfolio has the only insignificant 1- and 3-factor alphas. Pedersen, Asness & Moskowitz (2013, p. 940) found significant annualized alpha of 3.6% for their long-only U.S. value strategy between 1972 and 2011.

The portfolios have systematic risk (market beta) close to 1, which implies that they are not overly sensitive to the general market environment. Adding size (SMB) and value (HML) as explanatory variables in a 3-factor regression does not reduce the alphas, but slightly improves upon them. Yet, we do find a considerable positive loading on the value factor, which indicates that our portfolios tend to invest in cheap stocks - not surprisingly so (Pedersen, 2015, p. 29). The HML betas are all significant with t-values above 1.96 - except for the portfolio based on LY ROIC. The size factor buys small stocks and short sells large stocks (Fama & French, 1993), and thus we would have expected a negative SMB beta load, since our portfolios can only invest in the S&P 500 index of large companies. Nonetheless, we find very small SMB betas that are insignificantly different from zero.

Table 4.21: Factor loadings of the long-only value driver strategies

Value driver models Long-only	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Excess return	13.52%	14.44%	13.39%	13.45%	12.57%	14.08%	15.00%	17.57%
Alpha (MKT)	4.34%	3.64%	4.18%	4.35%	3.62%	4.66%	5.27%	8.35%
t-stat	3.70	1.63	3.46	3.54	2.98	3.25	3.23	3.14
3-factor alpha	4.43%	4.00%	4.30%	4.48%	3.78%	4.86%	5.52%	8.69%
t-stat	3.81	1.84	3.60	3.69	3.16	3.46	3.48	3.33
MKT beta	0.98	1.09	0.98	0.97	0.95	0.99	1.01	0.94
t-stat	36.80	21.99	35.80	34.89	34.85	30.77	27.88	15.68
SMB beta	0.06	0.12	0.07	0.06	0.05	0.07	0.08	0.15
t-stat	1.38	1.50	1.54	1.33	1.13	1.36	1.33	1.53
HML beta	0.07	0.25	0.09	0.10	0.11	0.14	0.18	0.24
t-stat	1.71	3.31	2.17	2.29	2.66	2.86	3.21	2.70
Sharpe ratio	0.94	0.80	0.93	0.94	0.89	0.94	0.96	1.03
Information ratio (3-factor)	0.99	0.47	0.93	0.95	0.81	0.88	0.88	0.85
Adj. R^2 (3-factor)	0.92	0.80	0.92	0.92	0.92	0.89	0.87	0.68

Factor loadings and performance measures for the long-only portfolios of stocks trading at a price/fair value below 1 based on the estimates of the value driver models. T-values below 1,96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

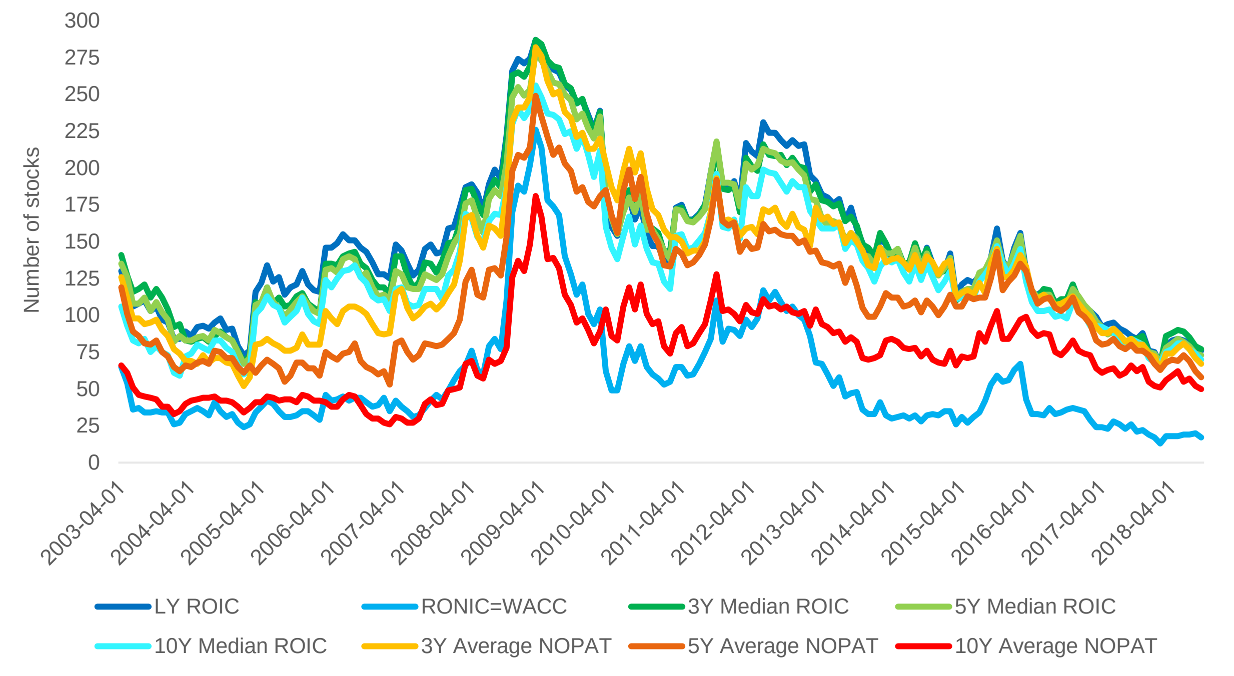
The information ratios on **Table 4.21**, which measure both the abnormal returns and the consistency of these abnormal returns, have been impressive at levels typically around 0.90. RONIC=WACC sticks out with a relatively lower information ratio of 0.47 due to its lower alpha and considerably higher standard error. In other words, the RONIC=WACC portfolio has not been as consistent at outperforming the benchmark.

As seen from the R-squared above, around 90% of the portfolios' return fluctuations are explained by the Fama & French 3-factor regression, but the RONIC=WACC (80.4%) and the 10Y Average NOPAT (67.5%) portfolios stick out with considerably lower R-squared.

Number of portfolio holdings

To evaluate risk and diversification in the value driver portfolios, **Figure 4.3** illustrates the monthly amount of stock holdings in each portfolio from 2004 to 2018. The amount of undervalued stocks in the eyes of each different portfolio generally move in the same pattern; they find more value during the financial crisis of 2007-2008, the peak of the European debt crisis in 2010-2012, and in 2015 when oil prices were at their lowest. These fluctuations in the amount of undervalued stocks are mainly due to fluctuations in stock prices, as our valuations are only updated once each year at the end of February.

Figure 4.3: Monthly number of stocks in the value driver portfolios



Illustrates the monthly amount of stocks trading below fair value included in the long-only value driver portfolios.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

Some of the portfolios in **Figure 4.3** stick out and appear more conservative by having considerably fewer stock holdings consistently across the 15-year period. These are especially the 10Y Average NOPAT and RONIC=WACC, but also the 5Y Average NOPAT generally finds fewer undervalued stocks. For several years, the 10Y Average NOPAT and RONIC=WACC have less than 50 stocks in their portfolios and, as a result, they are relatively more concentrated and less diversified than the rest of the value driver models, which could explain their relatively high volatility.

One thing to note is that the amount of value opportunities is relatively low during the time before the top of the bull market in July 2007, when the financial crisis started. As a result, some of the strategies are not as diversified heading into the bear market. This effect could contribute to the large risk and drawdowns seen in the RONIC=WACC portfolio in 2008. As stock prices fall, the strategies will gradually increase their number of holdings and become more diversified.

Figure 4.3 illustrates that the valuation models update and apply the fundamentals of the most recent fiscal year in March, which results in considerable upward or downward revisions in the valuations and in turn major changes in the amount of stocks that are considered under- or overvalued. This is best seen in March 2005, when the fundamentals from the fiscal year 2004 are incorporated in our fair value estimates and the amount of undervalued stocks jump significantly higher in almost all our models. However, it is fascinating that the 10Y Average NOPAT and RONIC=WACC portfolios generally appear much more stable in March where the yearly fundamental inputs are updated. It is intuitive that the 10Y Average NOPAT would put less emphasis on the most recent year's NOPAT and ROIC, as it also considers 9 other years of data. At the same time, RONIC=WACC only applies the most recent year's NOPAT in the value driver formula, but it couldn't care less for the ROIC achieved by the company itself, as it simply assumes the steady-state returns on capital to equal the sector's average cost of capital (WACC).

Sector exposure

To evaluate the value driver portfolios' risk and diversification across sectors, **Table 4.22** computes their over- and underweights in 10 Morningstar sectors relative to the equal weighted S&P 500 adjusted. The value driver models have over-weighted both healthcare and the consumer defensive sector relative to the S&P 500 adj. over the 15-year period. Both sectors generally have high cash flows, high ROIC, low WACC, and low multiples (P/B) in our data set, while they have been relatively stable across market cycles.

An overweight in energy stocks also sticks out and explains the models' relative underperformance in 2015, where oil prices took a large hit. With a higher exposure in energy, the value driver models differ from the Gordon Growth models which have a noteworthy underweight in energy. We expect that energy stocks typically make large investments during times when the oil price is high (such as in 2013), and this negatively influences their free cash flow and in turn the Gordon Growth valuations. The operating profit of energy stocks in 2013 was much more stable despite the major investments, which had a larger impact on the cash flow and balance sheet. Since we apply the operating profit in the value driver models instead of the free cash flow, the valuations were higher going into the oil price slump of 2014 and resulted in a considerable overweight in energy stocks as soon as oil prices and energy-stock prices started falling.

Table 4.22: Relative sector exposure of the value driver strategies

	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Technology	-3%	-2%	-3%	-3%	-3%	-3%	-4%	-4%
Consumer Cyclical	-2%	-1%	-2%	-2%	-3%	-2%	-2%	-2%
Healthcare	5%	1%	5%	5%	6%	5%	5%	7%
Energy	1%	8%	1%	1%	2%	2%	3%	4%
Communication Services	-1%	-1%	-1%	-1%	-2%	-1%	-1%	-2%
Consumer Defensive	5%	-3%	6%	6%	6%	6%	6%	6%
Industrials	-1%	-2%	-1%	-1%	0%	-1%	-2%	-4%
Basic Materials	0%	1%	0%	-1%	-1%	-1%	-1%	0%
Utilities	-1%	1%	-1%	-1%	0%	-1%	-1%	0%
Real Estate	-3%	-3%	-3%	-3%	-4%	-3%	-4%	-4%

Sector exposure of the long-only value driver models. Illustrates the overweighted (green) and underweighted (red) sectors relative to the S&P 500 adjusted in each of the long-only value driver models. A larger green bar indicates a heavier overweight in a sector. A larger red bar indicates a heavier underweight.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Morningstar sector samples.
Source: Morningstar Direct and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

The most underweighted sectors are technology and real estate. This might seem surprising considering that the technology stocks have some of the highest ROIC in our sample - but they also have the highest cost of capital (WACC) according to our Morningstar sector samples.

Fundamentals

This section evaluates the fundamental characteristics of the stocks that our value driver models invest in. This may provide us with valuable information as to whether undervalued stocks share similar characteristics with value or growth (Fama & French, 1993) and quality or junk (Pedersen, Asness & Frazzini, 2013). We measure the fundamentals of the last fiscal year at the time of investment, but as usual we lag the fundamentals by two months, so we will not have the numbers of fiscal year 2015 before the end of February 2016.

Value stocks have previously been found to be less profitable than growth stocks (Fama & French, 1995, Cohen, Polk & Vuolteenaho, 2003, and Pedersen et al., 2017), but we see the opposite pattern for our undervalued versus overvalued stocks in the value driver models.

In **Table 4.23**, undervalued stocks have EBIT and EBITDA margins and ROIC that are considerably higher than overvalued stocks, and this trend is very consistent when moving from the most overvalued deciles to the most undervalued deciles. Although the cheaper stocks are more profitable, they tend to have lower growth - especially according to the 3, 5, and 10Y Average NOPAT. These three models also stick out by not having as attractive margins and profitability as the other models. These factors somewhat confirm our previous thesis, that the 3, 5, and 10Y Average NOPAT models favor distressed value stocks (Chen & Zhang, 1998, p. 532).

Table 4.23: Difference in fundamentals between the high and low value deciles of the value driver strategies

Fundamentals Value driver models	LY ROIC H-L	RONIC = WACC H-L	3Y Median ROIC H-L	5Y Median ROIC H-L	10Y Median ROIC H-L	3Y Avg. NOPAT H-L	5Y Avg. NOPAT H-L	10Y Avg. NOPAT H-L
Book/Market	0.09	0.24	0.10	0.09	0.10	0.13	0.16	0.17
Sales/Market	0.95	1.22	0.04	0.79	0.79	1.04	1.08	1.11
FCFF/EV	4.2%	6.4%	4.0%	4.6%	4.6%	5.9%	6.1%	6.4%
EBITDA/EV	11.9%	14.3%	11.7%	10.8%	11.4%	10.9%	10.1%	7.3%
Earnings/Price	5.6%	5.9%	4.9%	5.2%	5.0%	3.8%	2.9%	0.9%
ROIC	16.5%	17.3%	17.1%	15.2%	14.6%	11.7%	12.0%	10.6%
EBITDA margin	1.2%	-3.5%	3.0%	3.1%	4.7%	0.1%	-0.7%	-2.4%
EBIT margin	8.3%	5.9%	6.8%	7.8%	8.7%	3.6%	2.7%	0.5%
1Y revenue growth	-0.9%	-2.9%	-0.7%	-1.1%	1.3%	-11.4%	-13.2%	-14.4%
NIBD/Equity	-0.51	-0.01	-0.68	-0.80	-0.58	-0.51	-0.43	-1.01

Illustrates the difference in the fundamental multiples and key ratios between the 10% most undervalued stocks and the 10% most overvalued stocks based on the price/fair value estimates of the value driver models. A positive number means that the undervalued stocks have a higher multiple or key ratio than the overvalued stocks.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Morningstar sector samples.
Source: Morningstar Direct and own estimations
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09

The 10% cheapest stocks across the value driver models also appear to be less leveraged with NIBD/Equity below 0.5 and often close to zero, while the 10% most overvalued stocks have an average NIBD/Equity of around 0.6 to 1.0. However, the most overvalued stocks in the RONIC=WACC portfolio do not have particularly high leverage.

Not surprisingly, the cheapest stocks also tend to trade at more attractive multiples and with higher yields, which is consistent with traditional value factors. Yet, the difference in book/market across deciles are consistently not very large in our various value driver models, which could explain why our portfolios perform differently from the HML value factor (Fama & French, 1993).

Value-sorted decile portfolios and High-Low

Table 4.24 shows the returns of stocks sorted into 10 deciles based on their price/fair value in the LY ROIC value driver model. Annualized excess returns and alphas rise almost monotonically when moving from the overvalued deciles to the undervalued deciles. Several alphas in the lower deciles are negative, which is an important driver of a successful long/short strategy, because we can buy undervalued stocks with high abnormal returns, and short stocks with negative abnormal returns. Only a few of the deciles' single- and 3-factor alphas are statistically significant with t-values above 1.96, but this is not surprising considering the smaller amount of stocks in each decile portfolio, which results in less robust performance. We take note of a considerable decrease in the alphas across the board when we measure against the more precise benchmark; the equal weighted S&P 500 adj., and this indicates again that the investment portfolios benefit from either excluding financials, equally weighting stocks instead of cap-weighting, or both.

Table 4.24: Price/fair value decile performance of the LY ROIC value driver model

LY ROIC Decile Performance	P1 Low value	P2	P3	P4	P5	P6	P7	P8	P9	P10 High value	H-L
Annualized excess return	**9.16%**	**12.47%**	**9.45%**	**9.16%**	**11.39%**	**12.14%**	**12.47%**	**14.71%**	**12.82%**	**15.74%**	**6.58%**
t-values	2.24	3.36	2.53	2.58	3.12	3.40	3.56	4.03	3.18	3.38	2.16
Alpha (MKT)	**-1.97%**	**2.11%**	**-1.23%**	**-0.72%**	**0.99%**	**2.09%**	**2.63%**	**4.63%**	**1.78%**	**3.77%**	**5.74%**
t-values	1.13	1.52	1.08	0.54	0.88	1.66	2.11	3.22	1.06	1.53	1.84
Alpha (S&P 500)	**-1.47%**	**2.51%**	**-0.81%**	**-0.34%**	**1.39%**	**2.47%**	**2.99%**	**5.02%**	**2.14%**	**4.24%**	**5.71%**
t-values	0.79	1.70	0.64	0.24	1.12	1.84	2.27	3.30	1.25	1.68	1.84
Alpha (S&P 500 adj.)	**-3.61%**	**0.69%**	**-2.57%**	**-2.11%**	**-0.31%**	**0.63%**	**1.29%**	**3.02%**	**0.03%**	**1.62%**	**5.22%**
t-values	2.29	0.53	2.21	1.72	0.27	0.58	1.11	2.59	0.02	0.77	1.67
3-factor alpha (MKT)	**-2.47%**	**1.72%**	**-1.53%**	**-1.03%**	**0.78%**	**1.99%**	**2.75%**	**4.62%**	**1.99%**	**4.03%**	**6.50%**
t-values	1.56	1.32	1.42	0.80	0.71	1.59	2.21	3.22	1.20	1.66	2.18
3-factor alpha (S&P 500 adj.)	**-4.02%**	**0.31%**	**-2.82%**	**-2.38%**	**-0.48%**	**0.54%**	**1.40%**	**3.02%**	**0.21%**	**1.90%**	**5.93%**
t-values	2.72	0.25	2.49	2.00	0.42	0.50	1.23	2.58	0.16	0.91	1.98
Beta (MKT)	**1.08**	**1.00**	**1.03**	**0.96**	**1.01**	**0.97**	**0.95**	**0.98**	**1.07**	**1.16**	**0.08**
t-values	29.86	34.78	43.51	34.25	42.91	37.10	36.74	32.57	30.69	22.64	1.26
Beta (S&P 500)	**1.09**	**1.02**	**1.05**	**0.97**	**1.03**	**0.99**	**0.97**	**0.99**	**1.10**	**1.18**	**0.09**
t-values	27.24	32.17	38.87	31.92	38.63	34.56	34.56	30.44	29.79	21.75	1.34
Beta (S&P 500 adj.)	**1.02**	**0.94**	**0.96**	**0.90**	**0.93**	**0.92**	**0.89**	**0.93**	**1.02**	**1.13**	**0.11**
t-values	33.73	37.74	43.00	38.15	42.44	44.24	39.84	41.65	37.49	27.86	1.81
Information ratio (MKT)	**-0.30**	**0.40**	**-0.28**	**-0.14**	**0.23**	**0.43**	**0.55**	**0.84**	**0.28**	**0.40**	**0.48**
Information ratio (S&P 500)	**-0.20**	**0.44**	**-0.17**	**-0.06**	**0.29**	**0.48**	**0.59**	**0.86**	**0.33**	**0.44**	**0.48**
Information ratio (S&P 500 adj.)	**-0.60**	**0.14**	**-0.58**	**-0.45**	**-0.07**	**0.15**	**0.29**	**0.68**	**0.01**	**0.20**	**0.44**
Adjusted R2 (3-factor)	**0.87**	**0.90**	**0.94**	**0.89**	**0.93**	**0.90**	**0.90**	**0.87**	**0.86**	**0.76**	**0.11**
Sharpe ratio	**0.57**	**0.85**	**0.64**	**0.66**	**0.79**	**0.86**	**0.90**	**1.02**	**0.81**	**0.86**	**0.55**

Decile performance of the price/fair value estimates of the LY ROIC value driver model. Low value is the decile of stocks with highest price/fair values. High value is the decile with lowest P/FV above zero. Negative price/fair values are excluded. High-Low (H-L) is a portfolio that buys the high value decile and short sells the low value decile. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

The most undervalued decile (10%) of stocks according to our LY ROIC model have the highest market risk with betas between 1.13 and 1.18 depending on which benchmark we use as a proxy for the market. All the betas are highly significant with double-digit t-values. These results are surprising considering that previous research of Fama & French (1992b) showed that cheap stocks have lower market betas than expensive stocks, although Pedersen et al. (2017, p. 21) found value stocks to have higher betas.

Although the betas do not rise monotonically going from the most overvalued deciles to the most undervalued deciles, the 20% most undervalued stocks do have relatively large betas and could indicate that some of their outperformance stems from higher market risk. It might influence the betas, that our sample (S&P 500) only allows us to pick among the market's largest and most traded stocks. The median 3-year beta of the S&P 500 constituents in September 2018 was 1.07 versus 0.81 for all US stocks.

The H-L portfolio in **Table 4.24** buys the 10% most undervalued stocks and short sells the 10% most overvalued stocks, which results in a annualized excess return of 6.6%, an abnormal return (alpha) of 5.2% above the S&P 500 adj. (insignificant with a t-value of 1.67), a market risk (beta) close to zero, and Sharpe and information ratios around 0.5. This performance appears strong for a long/short portfolio compared to previous research of factor models related to quality (Pedersen, Asness & Frazzini, 2013, p. T4) and value and momentum (Asness, Pedersen & Moskowitz, 2013, p. 940).

Table 4.25 illustrates the long/short H-L portfolios for each of the value driver models. Their superior performance is less robust across the 8 value driver models. In particular, the 3 models that apply a median historical ROIC to the most recent year's operating profit have low excess returns and almost zero abnormal returns over our three benchmarks. The reason is, that the most expensive decile of stocks (the short side of the H-L portfolios) in these 3 models perform relatively well with small, but positive alphas. At the same time, the best investments have not been within the 10% most undervalued stocks in these models but can be found within the 40% most undervalued stocks. The performance of RONIC=WACC is also weak. These results raise the question whether the value driver models are less effective at identifying expensive stocks with lower future returns compared to traditional risk factors.

Despite the less robust performance across the value driver models, we still find strong performance and abnormal returns within LY ROIC and the 2 portfolios based on 5- and 10-year average NOPAT. The 3Y Average NOPAT does produce some alpha and acceptable Sharpe- and information ratios too. None of the H-L portfolios are completely market neutral, because the beta of the most undervalued stocks is consistently higher than the most overvalued stocks.

Table 4.25: High-Low decile performance of the value driver models

Value driver portfolios Long/short H-L	LY ROIC H-L	RONIC = WACC H-L	3Y Median ROIC H-L	5Y Median ROIC H-L	10Y Median ROIC H-L	3Y Average NOPAT H-L	5Y Average NOPAT H-L	10Y Average NOPAT H-L
Annualized excess return	**6.58%**	**2.31%**	**1.77%**	**1.85%**	**2.21%**	**5.80%**	**10.32%**	**9.31%**
t-values	2.16	0.65	0.55	0.57	0.67	1.61	2.41	2.24
Alpha (MKT)	**5.74%**	**0.23%**	**0.39%**	**0.47%**	**0.83%**	**3.85%**	**7.49%**	**7.38%**
t-values	1.84	0.06	0.12	0.14	0.25	1.06	1.75	1.91
Alpha (S&P 500)	**5.71%**	**0.31%**	**0.39%**	**0.41%**	**0.82%**	**3.82%**	**7.50%**	**7.40%**
t-values	1.84	0.09	0.12	0.12	0.24	1.06	1.76	1.75
Alpha (S&P 500 adj.)	**5.22%**	**-0.38%**	**-0.05%**	**0.30%**	**0.37%**	**2.91%**	**6.01%**	**6.13%**
t-values	1.67	0.11	0.02	0.09	0.11	0.81	1.43	1.46
3-factor alpha (MKT)	**6.50%**	**1.26%**	**1.12%**	**1.31%**	**1.80%**	**4.98%**	**8.63%**	**8.50%**
t-values	2.18	0.38	0.35	0.41	0.57	1.49	2.13	2.13
3-factor alpha (S&P 500 adj.)	**5.93%**	**0.69%**	**0.65%**	**1.04%**	**1.27%**	**3.96%**	**7.12%**	**7.27%**
t-values	1.98	0.20	0.21	0.33	0.40	1.19	1.78	1.83
Beta (MKT)	**0.08**	**0.20**	**0.13**	**0.13**	**0.13**	**0.19**	**0.27**	**0.19**
t-values	1.26	2.70	1.96	1.94	1.91	2.50	3.08	2.13
Beta (S&P 500)	**0.09**	**0.21**	**0.14**	**0.15**	**0.14**	**0.20**	**0.29**	**0.20**
t-values	1.34	2.67	2.02	2.09	1.99	2.61	3.17	2.18
Beta (S&P 500 adj.)	**0.11**	**0.21**	**0.15**	**0.12**	**0.15**	**0.23**	**0.34**	**0.25**
t-values	1.81	3.12	2.31	1.93	2.28	3.34	4.25	3.16
Information Ratio (MKT)	**0.48**	**0.02**	**0.03**	**0.04**	**0.06**	**0.28**	**0.46**	**0.46**
Information Ratio (S&P 500)	**0.48**	**0.02**	**0.03**	**0.03**	**0.06**	**0.28**	**0.46**	**0.46**
Information Ratio (S&P 500 adj.)	**0.44**	**-0.03**	**0.00**	**0.02**	**0.03**	**0.21**	**0.37**	**0.38**
Adjusted R^2 (3-factor)	**0.11**	**0.17**	**0.10**	**0.13**	**0.15**	**0.19**	**0.16**	**0.14**
Sharpe ratio	**0.55**	**0.16**	**0.14**	**0.14**	**0.17**	**0.41**	**0.61**	**0.57**

Annualized H-L decile performance of the price/fair value estimates of the value driver models. High-Low (H-L) is a portfolio that buys the high value decile and short sells the low value decile. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

Long/short value driver portfolios

In this section, we construct portfolios that buy the 30% most undervalued stocks and short the 30% most overvalued stocks according to the P/FV estimates of the value driver models. With this approach, we replicate the general practice within factor papers such as Fama & French (1993) and Asness, Frazzini, and Pedersen (2015), which increases the comparability with these studies. The results are illustrated in **Table 4.26**.

The returns and alphas in **Table 4.26** have diminished compared to the highest performing H-L portfolios - mainly those based on 3-, 5-, and 10-year historical NOPAT and the LY ROIC portfolio. Yet, the alphas of the Median ROIC and RONIC=WACC portfolios have improved. The 3-factor alphas now range from 2.3% (RONIC=WACC) to 5.6% (10Y Average NOPAT). Four of the long/short portfolios have significant 3-factor alphas with a t-value above 1.96, but none of them pass the bar of 3 by Harvey, Liu, and Zhu (2015).

Table 4.26: Factor loadings of long/short value driver portfolios

Value driver portfolios 30/30 long/short	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	**4.02%**	**3.01%**	**2.40%**	**2.32%**	**2.31%**	**4.22%**	**4.61%**	**5.25%**
Alpha (MKT)	**3.74%**	**1.56%**	**1.75%**	**2.02%**	**2.35%**	**3.38%**	**3.72%**	**4.80%**
t-stat	1.92	0.71	0.86	0.99	1.21	1.50	1.65	2.13
3-factor alpha	**4.28%**	**2.31%**	**2.30%**	**2.63%**	**2.95%**	**4.10%**	**4.49%**	**5.56%**
t-stat	2.34	1.17	1.20	1.39	1.64	1.97	2.20	2.73
MKT beta	**0.00**	**0.08**	**0.03**	**-0.01**	**-0.03**	**0.03**	**0.03**	**-0.02**
t-stat	-0.11	1.75	0.58	-0.15	-0.73	0.72	0.54	-0.43
SMB beta	**-0.10**	**-0.06**	**-0.07**	**-0.11**	**-0.14**	**-0.11**	**-0.07**	**-0.06**
t-stat	-1.38	-0.77	-1.03	-1.52	-2.07	-1.39	-0.95	-0.75
HML beta	**0.31**	**0.45**	**0.32**	**0.35**	**0.34**	**0.42**	**0.46**	**0.46**
t-stat	4.97	6.63	4.87	5.33	5.44	5.85	6.52	6.49
Sharpe ratio	**0.54**	**0.35**	**0.31**	**0.30**	**0.31**	**0.48**	**0.53**	**0.61**
Information ratio (3-factor)	**0.57**	**0.28**	**0.30**	**0.34**	**0.40**	**0.47**	**0.52**	**0.65**
Adjusted R^2 (3-factor)	**0.13**	**0.24**	**0.13**	**0.15**	**0.16**	**0.18**	**0.21**	**0.20**

Illustrates the annualized performance of the long/short value driver portfolios and their beta loadings on MKT, SMB, and HML. The portfolios buy the 30% most undervalued stocks and short sell the 30% most overvalued stocks according to their respective valuation model. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

Asness (2014, p. 5) provides comparable results for size (small minus big), value (high minus low) and momentum (up minus down) between 1991 and 2013. His long/short factor portfolios produced annualized returns of respectively 3.3%, 3.6% and 6.3% and Sharpe ratios of 0.29, 0.32 and 0.36. For the size factor, this means that the difference in return between small stocks and large stocks averaged 3.3% per year. Half of the long/short portfolios do not live up to the performance of Cliff Asness' factors in terms of returns, but the other half certainly does so - not only with comparable returns but also with superior Sharpe ratios. The relatively high Sharpe ratios indicate that the relationship between the returns on our long and short positions is less volatile than the traditional value factor.

Traditional measures of value have underperformed growth for extended periods of time, which is best illustrated by Euclidean Technologies Management (2015). Such periods of underperformance result in more volatility and lower Sharpe ratios if you are long value and short growth. Just like value, our long/short portfolios have also experienced some 3- and 5-year periods of underperformance after 2009, but these have been of smaller magnitude.
The negative loadings on the size factor in **Table 4.26** correctly assumes the long/short portfolios to have a bias towards large companies, which could have negatively influenced our returns in the period considering the earlier mentioned premium of 3.3% per year for small stocks (Asness, 2014). The substantial positive loadings on value (HML) between 0.30 and 0.47 suggest that our portfolios are indeed long in cheap stocks (value) and short expensive stocks (growth).

Appendix 13 illustrates the performance of the long/short value driver portfolios when applying different benchmarks as an alternative to the Fama & French market benchmark. In short, there is no large differences in performance between applying the market or the traditional S&P 500 index as the benchmark. However, the abnormal returns over the equal-weighted S&P 500 benchmark excluding financials and duplicates are materially lower, and the betas are also higher. As we have previously stated, this indicates that removing financial stocks and equal weighting the portfolios have contributed to the performance of our valuation models.

Stressing growth and WACC assumptions

The base value driver models apply a growth of 3.95% in line with the average GDP growth from 2003-2017 and different sector WACC based on samples from Morningstar's equity research. In this section we will stress our assumptions to test how robust the performance of our models is to changes in the underlying assumptions.

The effect of changing the growth rate has a different effect in the value driver models compared to Gordon Growth, because higher growth demands larger investments in the value driver model. If the return on these investments (RONIC) is lower than the cost of capital (WACC), then the growth forces bad investments that destroy shareholder value instead of creating it (McKinsey, 2015, p. 22). Thus, increasing growth will favor quality firms with high returns on capital and hurt the valuations of less profitable firms. Decreasing growth will have the opposite effect.

When we assume a lower steady-state growth of 2.83%, the long-only value driver portfolios, as illustrated in **Table 4.27**, consistently deliver slightly higher returns although RONIC=WACC is an exception. In terms of single- and 3-factor alpha, we find material improvements in the models based on 3-, 5-, and 10-year Average NOPAT, while the rest are stale. Sharpe ratios are a notch lower due to higher volatility despite the improved returns. The lower growth does result in fewer undervalued firms across our 8 value driver models, and as a result, the portfolios become less diversified which explains the elevated volatilities.

Table 4.27: Stressing growth assumptions in the long-only value driver portfolios

Value driver portfolios Long-only	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	14.11%	14.48%	13.95%	13.70%	13.24%	14.95%	17.05%	19.71%
Alpha (MKT)	4.49%	3.66%	4.18%	4.08%	3.84%	5.18%	7.04%	9.86%
t-stat	2.97	1.60	2.75	2.71	2.44	2.74	2.81	2.58
3-factor alpha	4.66%	4.04%	4.35%	4.25%	4.08%	5.45%	7.43%	10.40%
t-stat	3.14	1.83	2.92	2.87	2.64	2.95	3.05	2.79
MKT beta	1.01	1.09	1.02	1.01	0.99	1.01	1.01	0.96
t-stat	29.69	21.60	29.91	29.84	27.91	23.92	18.18	11.24
SMB beta	0.08	0.14	0.10	0.08	0.06	0.08	0.13	0.23
t-stat	1.49	1.69	1.82	1.38	1.06	1.22	1.38	1.64
HML beta	0.12	0.26	0.13	0.12	0.16	0.19	0.27	0.38
t-stat	2.43	3.48	2.48	2.39	3.00	2.95	3.23	2.97
Sharpe ratio	0.92	0.80	0.90	0.89	0.87	0.93	0.97	0.96
Information ratio (3-factor)	0.81	0.46	0.75	0.74	0.67	0.75	0.77	0.71
Adjusted R^2 (3-factor)	0.88	0.80	0.89	0.88	0.87	0.83	0.74	0.54

Factor loadings and performance measures for the long-only portfolios of stocks trading at a price/fair value below 1 based on the estimates of the value driver models. T-values below 1.96 are insignificant at a 95% confidence level and marked in red

Weighting: Equal weighted and monthly rebalancing.
Growth: 2.83%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

The long/short portfolios based on the lower 2.83% growth rate are illustrated in **Appendix 14**. The performance is relatively robust across the value driver portfolios despite the lower growth. Yet, LY ROIC and the 3, 5, and 10Y Median ROIC, which are all applying the most recent year's NOPAT, experience some slightly lower alphas, Sharpe ratios and information ratios. When we explained the intuition behind the different value driver models, we mentioned that applying a historical average NOPAT would favor firms with low revenue growth or deteriorating operating profit. Lowering the steady-state growth assumptions might be more realistic for these slow-growing firms and thus result in less inaccurate valuations in the 3, 5, and 10Y Average NOPAT models and higher returns.

Appendix 14 contains the performance measures of the value driver models assuming growth rates of 0% and 6%. The three models based on historical NOPAT are much more robust when lowering growth assumptions, as their long-only and long/short returns and alphas improve considerably. However, these three long-only portfolios become much more concentrated as they identify fewer undervalued stocks with the 0% growth assumption, and this increases volatility - resulting in lower Sharpe ratios and information ratios. The long/short value driver portfolios based on historical NOPAT maintain their attractive Sharpe and information ratios, as they are based on deciles and do not care whether fewer stocks trade at a price/fair value below 1. The rest of the models, which all apply last year's NOPAT, experience relatively poor long/short performance with a growth rate of 0%, and their long-only returns become slightly higher but similarly more volatile due to fewer undervalued stocks in their portfolios.

If we assume all firms to grow at 6%, we dilute the portfolios' long-only returns but we also reduce volatility considerably, thus maintaining attractive Sharpe ratios and improving information ratios. Simultaneously, the beta loadings on the HML value factor diminish materially, and several of the long-only value driver portfolios have virtually no exposure to HML with an assumed growth rate of 6%. Six of the eight long/short value driver portfolios maintain attractive alphas between 3% and 6% and become significantly less correlated to the market with negative betas around -0.15. As mentioned earlier, higher growth requires more investments, thus favoring firms that can invest at attractive returns on capital - or in other words; quality companies. Thus, we find it fascinating that the long/short portfolios with higher growth assumptions achieve negative market betas like those of Quality Minus Junk (Pedersen, Asness & Frazzini, 2013, p. T6). However, we still maintain a strong, positive tilt towards the value factor as opposed to Quality Minus Junk.

We stress our WACC assumptions by applying the industry WACC from Damodaran (NYU) where we allocate the industries into our 10 different Morningstar sectors. The resulting sector costs of capital are roughly 3 percentage points larger on average than those previously applied from our sector samples from Morningstar's equity research. The average sector WACC is now 10.70%. An implication of such high levels of WACC is that if a firm's returns on capital in the value driver formula are lower than the WACC, any growth will result in the destruction of shareholder value (McKinsey, 2015, p. 22). This results in much lower valuations and fewer undervalued stocks across our value driver portfolios. As seen in **Appendix 15**, the higher WACC has a large positive impact on the long-only alphas and returns of the 3, 5, and 10Y Average NOPAT portfolios, but they become much more volatile as the portfolios often contain less than 25 stocks with lower Sharpe ratios as a result. This could have something to do with the much more concentrated exposure in technology and consumer cyclicals that account for around half of the portfolios across the 15-year period (see **Appendix 15**).

The long/short portfolios with the higher WACC assumptions of Damodaran in **Appendix 15** experience higher annualized returns but also higher systematic risk (market beta). In short, their higher returns become more dependent on the overall stock market, which results in lower alphas across the board. The Sharpe ratios are relatively stable and range from 0.26 for the long/short portfolio based on 10Y Median ROIC to 0.62 for the portfolio based on 10Y Average NOPAT.

We perform the same exercise with Bloomberg's sector consensus WACC in **Appendix 15**. The consensus WACC for the utility sector is considerably lower (5.18%), and this results in much higher exposure for the long-only value driver portfolios towards this sector. Performance-wise, however, the long-only and long/short portfolios are robust despite the overweight in utilities when applying the Bloomberg WACC.

Instead of assuming a different WACC for each sector, we could apply a low 7% WACC for all stocks. This would, on average, increase our valuations and make the models less conservative. Simultaneously, it would not punish cyclical sectors with higher systematic risk, such as technology and consumer cyclicals, that generally have a higher WACC according to Morningstar's equity research and Damodaran (NYU). The performance of the long-only and long/short value driver portfolios are illustrated in **Appendix 15** as well as the sector exposure of the long-only portfolios.

However, assuming every sector to have the same WACC of 7% does not result in unreasonably large sector tilts within the portfolios. Although the portfolios maintain an overweight in the consumer defensive sector, they start favoring consumer cyclicals and industrials. The long-only returns and alphas are reduced as the portfolios become more correlated to the market, which is an expected consequence considering that we lower the WACC considerably for the more market-sensitive cyclical sectors, in turn making them relatively more attractive in the eyes of our models. The long/short portfolios in **Appendix 15** also become more correlated to the market with betas between 0.10 and 0.18, while alphas are reduced considerably. Although the long-only and long/short portfolios with a homogeneous 7% WACC still outperform the market by delivering positive alpha, the simple assumption results in weaker performance compared to applying WACC from Morningstar.

Appendix 15 also illustrates performance and sector exposure with a 9% WACC across sectors. This results in a much more considerable bias towards cyclical sectors such as technology, consumer cyclicals, energy, and industrials. However, the performance of both long-only and long/short portfolios is still consistently strong.

4.3 Performance of Morningstar's Rating for Stocks

This section evaluates the performance of various investment strategies based on Morningstar's rating for stocks and their price/fair value estimates.

With monthly rebalanced portfolios, Morningstar's equity recommendations on the S&P 500 firms did not perform as expected. As seen in **Table 4.28,** the 5-star portfolio (very undervalued) surprisingly showed the lowest annualized excess return (9.7%) among all the star ratings. The 1-star rating, which includes the most expensive stocks relative to Morningstar's fair value, stands out as the one with the highest annualized returns (21.8%). Though on a risk-adjusted basis, the results are a little less one-sided. Both the 5- and 1-star stocks, on average, experience the two highest volatilities of 20.5% and 38.5% respectively - resulting in inferior Sharpe ratios of 0.47 and 0.57. The remaining 4-, 3-, and 2-star portfolios have similar returns around 12% and Sharpe ratios of almost 0.80.

Morningstar's ratings, except for the 5-star portfolio, performed relatively well compared to the market and the whole S&P 500 index with annualized returns above 11%. But the results indicate that Morningstar has benefitted from the exclusion of financials, as only the 1-star and 4-star portfolios outperform our adjusted S&P 500 benchmark on raw returns. The Sharpe ratios generally lag those of the two S&P 500 benchmarks owing to higher volatility - probably because each portfolio includes fewer stocks than the indexes and thus are less diversified. The portfolio based on Morningstar price/fair values below 1 in **Table 4.28** will be analyzed in a later section.

Table 4.28: Return and risk of Morningstar's recommendations versus the benchmarks

	1 star	2 stars	3 stars	4 stars	5 stars	Morningstar P/FV	Market	S&P 500	S&P 500 adj.
Ann. excess return	21.84%	12.17%	11.52%	12.63%	9.68%	12.09%	10.33%	9.75%	12.53%
Ann. volatility	38.50%	16.28%	14.61%	16.18%	20.54%	15.27%	13.58%	13.20%	14.64%
Sharpe ratio	0.57	0.75	0.79	0.78	0.47	0.79	0.76	0.83	0.86
Cumulative return	15.76	6.38	6.01	6.87	3.85	6.47	5.11	5.66	7.01

Illustrates the annualized figures of the average monthly returns in excess of the risk-free rate, standard deviation (volatility), Sharpe ratio and cumulative returns for Morningstar's equity ratings**,** price/fair value estimates below 1, and three benchmarks. The Market benchmark is from the Kenneth French database and S&P 500 Adj. is the exact match of an equal weighted portfolio of all the stocks included in our investable universe each month which excludes duplicates and financials.

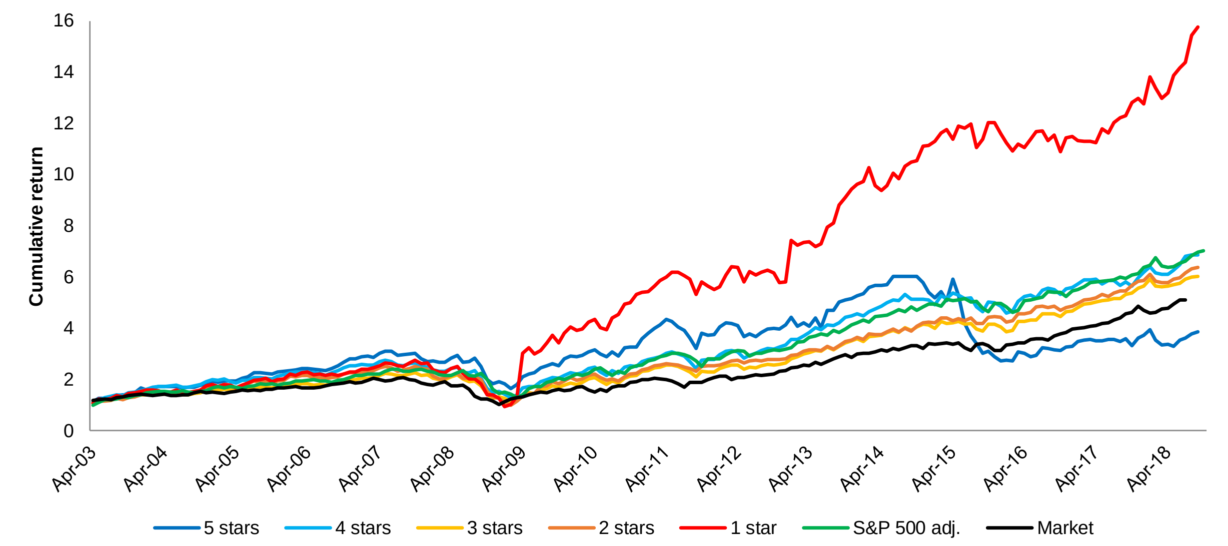
Weighting: Equal weighted and monthly rebalancing.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

The cumulative returns of the star ratings on **Figure 4.4** illustrate that the 5-star rating outperformed all but the 1-star rating until 2015, where the 5-star portfolio in less than 12 months gave up all its outperformance and then some. Morningstar's own research points towards an overly optimistic outlook on oil prices leading to many concentrated 5-star bets in the energy sector heading into the oil price crash in 2014 and 2015 according to Morningstar's Elizabeth Collins and Charles Gross (2018, p. 7). Due to the smaller data sample in our paper, the 5-star rating was even more concentrated in energy-stocks in the summer of 2015, which led to several months with losses in the range of 10-20% for the 5-star portfolio.

Another story is that the 1-star rating did not start outperforming before the bottom of the crisis in 2009 - shooting upwards with only a single stock-pick, which was Ford Motor yielding a 32% in March followed by 127% in April of 2009. Since then, the 1-star rated stocks in the S&P 500 index have outperformed handsomely.

From April 2003 to February 2009, both the 5- and 4-star ratings outperformed the rest of the ratings - with the 5 stars on top. This is closer to what we had expected when first looking into the performance of Morningstar's stock recommendations. For many years following the crisis, the 5-star rated stocks performed well, but the concentrated bets on expensive stocks simply made the 1-star rating perform much better. The 4-star rating keeps consistently outperforming the 2- and 3-star rating until the end of our sample period in September 2018 but is roughly on par with the benchmark (S&P 500 adj., which is equal weighted and excludes financials).

Figure 4.4: Cumulative returns of Morningstar's ratings for stocks



Cumulative monthly total returns of Morningstar's ratings for stocks in the S&P 500 excluding financials.

Weighting: Equal weighted and monthly rebalancing.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

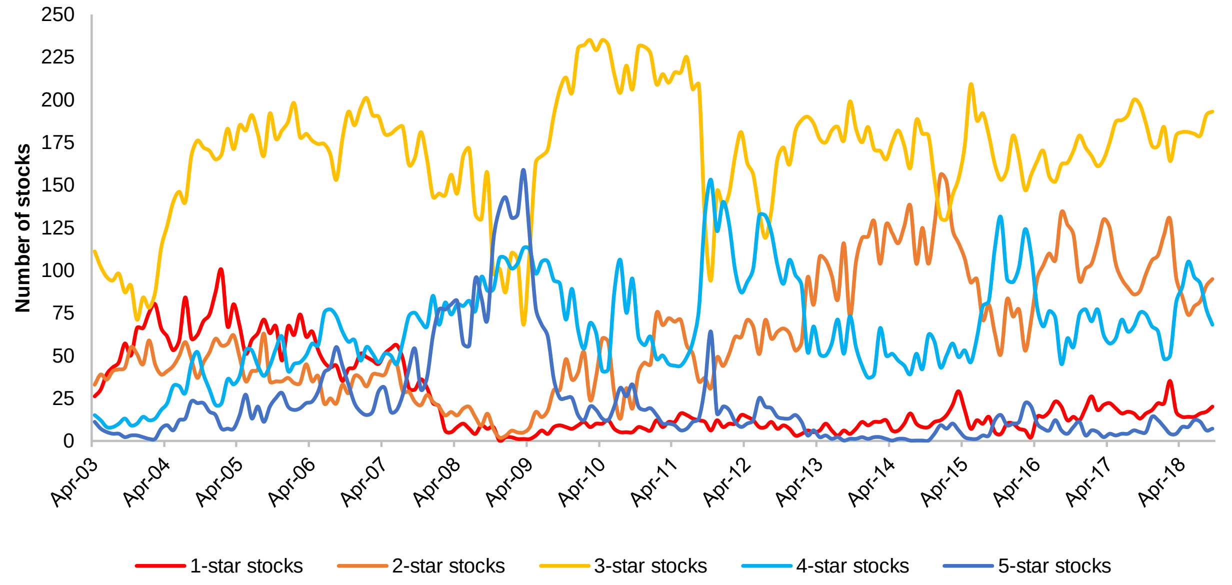
One aspect of performance is return, another is risk

The high volatility of 5-star stocks surprised us considering Morningstar's methodology. To receive the 5-star rating, stocks with a higher uncertainty rating must have a relatively larger discount relative to Morningstar's estimated fair value. With a low uncertainty rating, stocks with a discount of 20% or more will receive 5 stars, but with a high uncertainty rating, the required discount increases to 40% (see **Appendix 2**). Morningstar's adjustments for uncertainty would make it very difficult for a firm with "extreme uncertainty" to receive a 5-star rating, as this would require it to trade with a discount of 75% to fair value. Yet, the uncertain and volatile stocks have seemingly made their way into 5-star territory from time to time. Although, the most frequent visitors in the 5-star rating has been from one of the more defensive sectors; healthcare (we will illustrate this later), with names such as Johnson & Johnson, Pfizer and Allergan.

The explanation for the 1- and 5-star's volatile returns may very well lie in the number of stocks given the two ratings. As seen in **Figure 4.5**, the number of 1- and 5-star rated stocks are often below 25. When the market appears cheap, such as in the depths of the Global Financial Crisis, the amount of 5-star opportunities are plenty, but in other periods, only a handful appear. The reverse is true for the most expensive stocks that make up the 1-star rating. For a period in 2014, the number of 5-star opportunities even dried up completely, meaning that the returns of the 5-star portfolio were nonexistent in this period which could explain some of the underperformance. With much fewer than 25 stocks in the portfolios, you can hardly argue that they are well diversified, and this increases idiosyncratic risk as illustrated by Sharpe (1995, p. 86).

The consistently large amount of 3-star rated companies indicate that many stocks tend to trade close to their fair value, but in times of great uncertainty and negative sentiment such as in 2008, these stocks can quickly appear undervalued and switch into the 4- and 5-star territory.

Figure 4.5: Number of stocks with Morningstars star ratings



Monthly number of stocks in Morningstar's rating of stocks in the S&P 500 excluding financials.

Weighting: Equal weighted and monthly rebalancing.
Source: Morningstar Direct, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Adjusting Morningstar's performance for common risk factors

If we analyze the market risk, or beta, of the star ratings in **Table 4.29**, the 1-star rated stocks stand out with a whopping 1.5, which is the largest in the strategies we have backtested. The large market beta suggests that the impressive returns of 1-star stocks depend greatly on the general market conditions.

Table 4.29 also indicates that some of the outperformance can be explained by the portfolios' higher systematic risk, since this should be compensated with a higher return according to the CAPM (Sharpe, 1964). For the portfolios of stocks rated with 2 to 5 stars, betas range between 1.04 (3 stars) and 1.13 (5 stars). The most undervalued stocks (5-stars) surprise us again with a slightly higher beta despite having inferior returns - indicating that the portfolio is not sufficiently compensated with higher returns for taking more systematic risk. This results in the 5-star stocks generating a single-factor alpha of -1.9%.

At the other end of the spectrum, the 1-star portfolio generates an alpha of 6.1% which even increases to 6.5% when adding the 3 factors of Fama & French as explanatory variables (both alphas are insignificant). One thing to note is that the alpha of the 1-star portfolio could easily be attributable to luck or randomness given the low number of stocks that we found earlier. The annualized alphas of the 2-, 3-, and 4-star portfolios stand around 1% but are also insignificantly different from zero at a 95% confidence interval.

Table 4.29: Performance of Morningstar's rating for stocks and price/fair value estimates

Morningstar portfolios Performance	1 star	2 stars	3 stars	4 stars	5 stars	5 & 4 stars	1 & 2 stars	Price/fair value	1 minus 5 stars
Annualized excess return	**21.8%**	**12.1%**	**11.5%**	**12.6%**	**9.7%**	**13.1%**	**13.0%**	**12.1%**	**12.1%**
t-values	2.23	2.94	3.11	3.07	1.86	3.21	2.83	3.12	1.37
Alpha (MKT)	**6.1%**	**1.1%**	**0.8%**	**1.2%**	**-1.9%**	**1.8%**	**1.0%**	**1.0%**	**8.1%**
t-values	0.73	0.57	0.81	0.78	-0.54	1.13	0.45	0.85	0.90
Alpha (S&P 500)	**6.9%**	**1.5%**	**1.2%**	**1.7%**	**-1.5%**	**2.2%**	**1.5%**	**1.4%**	**8.4%**
t-values	0.81	0.75	1.08	1.00	-0.42	1.33	0.63	1.11	0.93
Alpha (S&P 500 adj.)	**1.8%**	**-0.4%**	**-0.7%**	**-0.5%**	**-4.0%**	**0.0%**	**-0.9%**	**-0.7%**	**5.8%**
t-values	0.22	-0.22	-1.03	-0.38	-1.19	0.00	-0.40	-0.92	0.65
3-factor alpha (MKT)	**6.5%**	**1.2%**	**0.8%**	**1.3%**	**-1.7%**	**1.9%**	**1.2%**	**1.0%**	**8.1%**
t-values	0.76	0.63	0.82	0.83	-0.47	1.20	0.52	0.90	0.90
3-factor alpha (S&P 500 adj.)	**2.2%**	**-0.2%**	**-0.7%**	**-0.4%**	**-3.8%**	**0.1%**	**-0.6%**	**-0.7%**	**6.1%**
t-values	0.28	-0.12	-1.02	-0.28	-1.14	0.10	-0.29	-0.86	0.67
Beta (MKT)	**1.52**	**1.07**	**1.03**	**1.10**	**1.13**	**1.10**	**1.16**	**1.08**	**0.39**
t-values	8.61	26.92	48.96	33.86	15.14	33.79	23.83	45.43	2.09
Beta (S&P 500)	**1.53**	**1.09**	**1.05**	**1.12**	**1.15**	**1.12**	**1.18**	**1.10**	**0.38**
t-values	8.36	26.09	43.56	31.44	14.85	31.57	22.81	41.07	1.97
Beta (S&P 500 adj.)	**1.60**	**1.00**	**0.98**	**1.05**	**1.09**	**1.05**	**1.10**	**1.02**	**0.51**
t-values	10.39	28.10	70.40	40.79	16.87	42.16	27.20	67.54	2.94
Information ratio (MKT)	**0.19**	**0.15**	**0.21**	**0.20**	**-0.14**	**0.29**	**0.12**	**0.22**	**0.23**
Information ratio (S&P 500)	**0.21**	**0.20**	**0.28**	**0.26**	**-0.11**	**0.35**	**0.16**	**0.29**	**0.24**
Information ratio (S&P 500 adj.)	**0.06**	**-0.06**	**-0.27**	**-0.10**	**-0.31**	**0.00**	**-0.11**	**-0.24**	**0.17**
Adjusted R^2	**0.31**	**0.82**	**0.95**	**0.89**	**0.57**	**0.88**	**0.78**	**0.94**	**0.04**
Annualized volatility	**38.5%**	**16.3%**	**14.5%**	**16.2%**	**20.5%**	**16.1%**	**18.1%**	**15.3%**	**35.0%**
Sharpe ratio	**0.57**	**0.75**	**0.79**	**0.78**	**0.47**	**0.82**	**0.72**	**0.79**	**0.35**

Performance of Morningstar's rating for stocks and price/fair value below 1. The t-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Applying the S&P 500 adj. as a benchmark provides a better fit with our investable universe, because it is equal weighted and excludes financials. With this benchmark, alphas and information ratios generally become considerably lower – indicating that the Morningstar portfolios benefit from the dynamic of equal weighting and excluding financials. As such, even the alphas of the 1-star rating become close to 2% in **Table 4.29.**

If a stock receives a 5-star rating due to a falling stock price, this negative price momentum could remain and hurt the returns in the medium term (Asness, 1994). The opposite could be true for 1-star rated stocks. For this reason, we've also computed the 1-month lagged returns for each star rating. For example, if a stock has a 5-star rating at the end of February, we will compute its return in April instead of the previous month. The effect is the opposite of what you might expect. The risk adjusted performance of the 5-star rating becomes slightly worse and the 1-star rating improves a little.

We initially thought the 1-star stocks to be carrying positive momentum and the 5-star stocks to have negative momentum, as this seems intuitive - expensive stocks have seen their prices rise, and cheap stocks have suffered falling prices. The latter might still be the case, but the former did not exactly show itself in the data when regressing the returns of the star-based portfolios on the market, size, value and momentum factor from Kenneth French's database. This is shown in **Table 4.30**, where we find a relatively large, negative beta loading on the momentum factor for the 5-star and surprisingly also the 1-star portfolio. This indicates that these two portfolios tend to invest in stocks with low prior returns, or for other reasons are negatively correlated with momentum stocks. It looks as if the negative correlation with momentum becomes gradually smaller as we move down from the 5-star rating. The 2-star loading on momentum is insignificantly different from zero.

Table 4.30: 4-factor performance of Morningstar's ratings and price/fair value estimates

Morningstar portfolios 4-factor performance	1 star	2 stars	3 stars	4 stars	5 stars	5 & 4 stars	1 & 2 stars	Morningstar P/FV	1 minus 5 stars
Annualized excess return	**21.8%**	**12.1%**	**11.5%**	**12.6%**	**9.7%**	**13.1%**	**13.0%**	**12.1%**	**12.1%**
Alpha (MKT)	**6.1%**	**1.1%**	**0.8%**	**1.2%**	**-1.9%**	**1.8%**	**1.0%**	**1.0%**	**8.1%**
t-values	0.73	0.57	0.81	0.78	-0.54	1.13	0.45	0.85	0.90
4-factor alpha	**9.6%**	**1.2%**	**1.1%**	**1.9%**	**-0.5%**	**2.5%**	**1.5%**	**1.6%**	**10.1%**
t-values	1.27	0.65	1.22	1.37	-0.15	1.95	0.66	1.67	1.16
MKT beta	**1.05**	**1.03**	**0.98**	**1.00**	**0.98**	**0.99**	**1.06**	**1.00**	**0.07**
t-values	5.87	22.77	44.36	30.88	12.61	32.09	19.74	45.31	0.32
SMB beta	**0.58**	**0.12**	**0.10**	**0.16**	**0.02**	**0.14**	**0.21**	**0.10**	**0.56**
t-values	2.04	1.73	2.92	3.13	0.20	2.80	2.48	2.93	1.69
HML beta	**-0.34**	**0.09**	**-0.04**	**-0.04**	**-0.08**	**-0.06**	**0.06**	**-0.05**	**-0.26**
t-values	-1.23	1.26	-1.20	-0.85	-0.64	-1.18	0.78	-1.60	-0.82
MOM beta	**-1.08**	**-0.01**	**-0.11**	**-0.20**	**-0.40**	**-0.23**	**-0.11**	**-0.18**	**-0.68**
t-values	-6.86	-0.29	-5.53	-7.10	-5.82	-8.66	-2.33	-9.39	-3.75
Sharpe ratio	**0.57**	**0.75**	**0.79**	**0.78**	**0.47**	**0.82**	**0.72**	**0.79**	**0.35**
Information ratio (4-factor)	**0.34**	**0.17**	**0.32**	**0.36**	**-0.04**	**0.51**	**0.17**	**0.44**	**0.31**
Adjusted R^2 (4-factor)	**0.31**	**0.82**	**0.95**	**0.89**	**0.57**	**0.88**	**0.78**	**0.94**	**0.04**

Illustrates the annualized performance of portfolios based on Morningstar's equity ratings and price/fair value estimates below 1. The four factors are from the Kenneth French database. MOM is the average of the returns on two portfolios (big and small) of stocks with high prior returns minus the average of the returns on two portfolios of stocks with low prior returns. The t-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

The large negative correlation with the momentum factor could simply be due to some noisy outliers in the returns of the 1-star stocks due to the small portfolio size we found earlier, but we also find a more intuitive explanation. The worst enemy of momentum is trend reversals (a so-called "whipsaw"), where the market suddenly turns on a plate and previous winners quickly become losers. In our sample, we see some of these episodes unfold in April and May 2003 when the bears of the Dot-com bubble finally turned bull and in March and April 2009 (as previously described). During these months, momentum performed incredibly bad with double-digit negative returns while the 1-star rated stocks experienced rich returns. If we remove these few episodes from the data, the returns on momentum and 1-star stocks suddenly look much more correlated.

As we had expected, the 5-star rated stocks have a strong negative correlation with the momentum factor, as the MOM (Kenneth French, 2018) beta is -0.40 with a t-value of -5.82. In a lesser extent, the same could be said for 4-star stocks and undervalued stocks (with P/FV below 1). The market beta explains materially less of the 1- and 5-star returns in the 4-factor regression, because much of the variation is instead explained by negative momentum.

The 4-factor alphas grow compared to the 3-factor alphas and the 5- & 4-star portfolio almost becomes significant at a 95% level with a t-value of 1.95. This can be attributed to the negative loadings on momentum. According to Asness (1994), a negative exposure to momentum should result in lower excess returns, but since the MOM factor cannot explain the abnormal returns of for example the 5- & 4-star portfolio, the 4-factor alpha rises.

The beta-loadings on size (SMB) and value (HML) are hardly of noticeable magnitude, which is disappointing since we had expected to see some value bias in the 4- and 5-star rating. We do, however, see some material positive correlation between size and the 1- and 4-star portfolios with SMB betas of 0.58 and 0.16 respectively, but this is hard to explain considering our sample only consists of large firms. Small firms should be favored in risk-on events where investors become more confident and allocate to more risky categories such as in May 2003 and April 2009, and this could be a factor at play.

If we look at the 4-factor performance measures, the information ratio is highest for the 5 & 4 stars, P/FV, and 4 stars portfolios with a ratio of 0.51, 0.44 and 0.36 respectively and these also have Sharpe ratios around 0.80. The 1-star stocks might look good on raw returns and alpha, but once adjusting for volatility and common risk factors, Morningstar's buy recommendations start looking more attractive.

Mixing stars increases diversification

Table 4.29 and **Table 4.30** also illustrate two more diversified versions of undervalued and overvalued stocks (according to Morningstar's equity research) by sorting the 4- and 5-star stocks into one portfolio and the 1- and 2-star stocks into another.

The equal weighted combination of both 4- and 5-star rated stocks is significantly more competitive and beats most of the standalone star ratings on both risk (16.1% standard deviation) and return (13.1%). This strategy would allow a profitable 5-star investment, that has been downgraded to 4 stars due to a rising price, to stay in the portfolio and rise further. In other words, this lets the profit run. The mix even improves upon the volatility of the 4-star portfolio (16.2%) despite the 5-star stocks having significantly higher volatility (20.5%). An explanation for the slightly lower standard deviation is diversification, as the 5- & 4-star portfolio simply contains more stocks than the two ratings on a standalone basis. The resulting Sharpe ratio of 0.82 beats any of the other strategies based on Morningstar's ratings while the market alpha of 1.8% is only second to that of the 1-star rating. Unfortunately, the alpha disappears when regressing on the S&P 500 index excluding financials (our data sample), indicating that any outperformance stems from our exclusion of financials and the S&P 500 performance differing from the general market.

If we carry out the same exercise with the 1- and 2-star ratings, we only manage to improve upon the 1-star ratings systematic risk (beta) and volatility which ultimately increases the Sharpe ratio to a level of 0.72, which is lower but comparable to the other strategies. The annualized return of 13.0% does not match the one of the 5- & 4-stars portfolio. At the same time, the alpha of the 1-star rating almost wanes completely. If you want to bet against the star ratings, buying the 2-star rated stocks does not seem like the best way to go about it.

Morningstar's sector weighting

We have investigated which sectors Morningstar's analysts have favored or shunned in the past 15 years relative to our equal-weighted sample. These are illustrated in the **Table 4.31** for the 5 different star-portfolios and the price/fair value-based portfolio.

The 1-star portfolio has a heavy 10% overweight in tech stocks over the whole sample period whereas the other portfolios all underweight this sector. Meanwhile, technology has been the best performing sector with an average annualized return of 15.5%. The 1-star portfolio heavily underweights consumer defensives, cyclicals, and industrials. The consumer defensive sector had the lowest annualized returns in the period, while both consumer cyclicals and industrials enjoyed relatively high returns as we illustrated in **Section 4.1**. Since the 1-star returns have been materially higher than even the best performing sector, the portfolio's high returns cannot solely be attributed to its sector allocation. The portfolio has not only been favoring the right sectors but has also picked high performing stocks within sectors.

Although the 5-star portfolio was heavily concentrated in energy stocks around the oil price shock in 2015, the portfolio has not generally favored energy with an overweight of just 1% throughout the 15-year backtest. The 5-star's immense overweight of 7% in healthcare also sticks out. Many of the healthcare stocks in the S&P 500 have a low Morningstar uncertainty rating and a narrow or wide economic moat due to their patents and R&D, and these factors contribute to a higher valuation and star rating. Thus, the 5-star overweight in healthcare is not surprising. The Morningstar P/FV and 4-star portfolios generally imitate the 5-star portfolio in their over- and underweighting of sectors, but they have less extreme sector tilts except for their 4% underweight in technology.

Table 4.31: Relative sector exposure of Morningstars ratings and price/fair value estimates

Morningstar portfolios Sector exposure	1 star	2 stars	3 stars	4 stars	5 stars	Morningstar P/FV
Technology	10%	-2%	-3%	-4%	-2%	-4%
Consumer Cyclical	-5%	-2%	0%	2%	3%	2%
Healthcare	1%	-1%	0%	3%	7%	2%
Energy	4%	-3%	0%	1%	1%	1%
Communication Services	-2%	-2%	-1%	0%	-1%	0%
Consumer Defensive	-5%	2%	1%	1%	2%	1%
Industrials	-5%	2%	3%	1%	-1%	2%
Basic Materials	1%	0%	-1%	-2%	-2%	-1%
Utilities	-1%	5%	2%	-1%	-3%	0%
Real Estate	1%	0%	-1%	-2%	-4%	-2%

Illustrates the overweighted (green) and underweighted (red) sectors relative to the S&P 500 adj. (equal weighting stocks and excluding financials and duplicates) in each of the portfolios based on Morningstar's ratings and P/FV below 1. A larger green bar indicates a heavier overweight in a sector. A larger red bar indicates a heavier underweight. The P/FV portfolio equal weights stocks with a price/fair value below 1.

Weighting: Equal weighted and monthly rebalancing.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Buying 1-star and short selling 5-star stocks

Due to the results found above, one could construct a portfolio that exploits the negative alpha of the 5-star rated stocks by going short, while buying the 1-star rated portfolio to extract its abnormal returns. The portfolio is dollar neutral, meaning that the long and short side is equal weighted. This "1 minus 5 stars" can be found in **Table 4.29** and **Table 4.30** and naturally does not achieve the same average returns or Sharpe ratios as the other strategies due to being short 5-star stocks which have inferior, but positive, returns.

This strategy indeed manages to improve the alpha materially in respect to both the 1-factor CAPM (from 6.1% to 8.1%), the S&P 500 adj. (1.8% to 5.8%), and the Fama & French 3-factor model (from 6.5% to 8.1%). It also improves upon the statistical significance (t-stat) of these values - although they are still insignificant at a 95% confidence interval. In other words, the maneuver of shorting 5-star stocks makes the abnormal returns both larger and more robust. On the other hand, 1 minus 5 stars still carries major risk with its annualized standard deviation of 35% - likely due to the low amount of 1- and 5-star rated stocks as we illustrated earlier.

Since the portfolio is constructed as dollar neutral (1 dollar short in the 5-star portfolio and 1 dollar long in the 1-star portfolio), and since the 1-star has significantly higher beta than the 5-star, this strategy does not manage to eliminate all the systematic (beta) risk. Thus, we do not extract an abnormal return which is completely independent of the general market environment. One could construct a market-neutral portfolio with a beta of zero by applying leverage to the long and short sides (Pedersen & Frazzini, 2013, p. 11).

Morningstar price/fair value

Investing in every S&P 500 firm trading below Morningstar's fair value and rebalancing monthly yields a below-average excess return of 12.1% with a relatively low volatility (15.3%) as seen in **Table 4.28**. The results should be comparable with the 5- & 4-stars portfolio, as this strategy only adds the undervalued part of the 3-star stocks. What makes the price/fair value approach interesting is when we decompose it into deciles from the most undervalued to most overvalued stocks. This will show more details on whether the S&P 500 stocks perform better when moving from very overvalued to very undervalued in the eyes of Morningstar's analysts - although the analysis of the star ratings above indicated that they do not.

Table 4.32 clearly illustrates the higher volatility in the most overvalued and undervalued stocks. The same goes for the betas that are highest for the most extreme deciles but otherwise tend to be higher within the deciles with lower price/fair values. These results indicate that undervalued stocks are more sensitive to the market, consistent with our findings within the quantitative terminal value strategies.

Table 4.32: Decile performance of Morningstar's price/fair value estimates

Morningstar price/fair value Decile performance	P1 low value	P2	P3	P4	P5	P6	P7	P8	P9	P10 high value	H-L
Annualized excess return	**13.5%**	**13.3%**	**12.1%**	**11.7%**	**13.5%**	**10.9%**	**10.6%**	**13.6%**	**12.7%**	**13.7%**	**0.2%**
t-values	2.83	3.66	3.54	3.35	3.71	3.12	2.68	3.43	2.82	2.57	0.05
Alpha (MKT)	**0.9%**	**3.7%**	**2.8%**	**1.7%**	**3.4%**	**0.9%**	**-0.5%**	**2.4%**	**0.2%**	**0.0%**	**-0.9%**
t-values	0.40	2.10	1.92	1.59	2.44	0.85	-0.38	1.75	0.11	0.01	-0.25
Alpha (S&P 500)	**1.5%**	**4.1%**	**3.1%**	**2.1%**	**3.8%**	**1.2%**	**-0.1%**	**2.8%**	**0.6%**	**0.6%**	**-0.9%**
t-values	0.62	2.23	2.07	1.81	2.57	1.11	-0.07	1.95	0.36	0.22	-0.25
Alpha (S&P 500 adj.)	**-1.0%**	**2.2%**	**1.4%**	**0.5%**	**1.8%**	**-0.3%**	**-2.2%**	**0.8%**	**-1.9%**	**-2.7%**	**-1.6%**
t-values	-0.50	1.39	1.07	0.44	1.59	-0.30	-1.87	0.68	-1.43	-1.18	-0.45
3-factor alpha (MKT)	**0.9%**	**3.5%**	**2.6%**	**1.6%**	**3.2%**	**0.8%**	**-0.6%**	**2.4%**	**0.4%**	**0.3%**	**-0.5%**
t-values	0.40	2.07	1.85	1.51	2.36	0.77	-0.44	1.71	0.22	0.12	-0.15
3-factor alpha (S&P 500 adj.)	**-0.8%**	**2.1%**	**1.3%**	**0.4%**	**1.7%**	**-0.4%**	**-2.2%**	**0.7%**	**-1.7%**	**-2.3%**	**-1.4%**
t-values	-0.40	1.35	0.99	0.37	1.47	-0.40	-1.95	0.62	-1.35	-1.02	-0.39
Beta (MKT)	**1.22**	**0.92**	**0.90**	**0.96**	**0.98**	**0.97**	**1.07**	**1.08**	**1.21**	**1.33**	**0.10**
t-values	25.32	24.99	30.11	42.95	34.07	43.53	37.65	37.38	33.70	22.52	1.37
Beta (S&P 500)	**1.23**	**0.93**	**0.92**	**0.99**	**1.00**	**1.00**	**1.10**	**1.11**	**1.24**	**1.34**	**0.11**
t-values	23.13	23.47	28.72	40.19	31.79	41.98	34.87	35.67	31.86	21.22	1.42
Beta (S&P 500 adj.)	**1.17**	**0.88**	**0.85**	**0.89**	**0.94**	**0.90**	**1.02**	**1.02**	**1.17**	**1.31**	**0.14**
t-values	28.85	29.13	33.90	41.79	43.05	42.65	45.73	43.85	46.35	30.08	2.07
Information ratio (MKT)	**0.10**	**0.55**	**0.50**	**0.42**	**0.64**	**0.22**	**-0.10**	**0.46**	**0.03**	**0.00**	**-0.06**
Information ratio (S&P 500)	**0.16**	**0.58**	**0.54**	**0.47**	**0.67**	**0.29**	**-0.02**	**0.51**	**0.09**	**0.06**	**-0.07**
Information ratio (S&P 500 adj.)	**-0.13**	**0.36**	**0.28**	**0.12**	**0.42**	**-0.08**	**-0.49**	**0.18**	**-0.38**	**-0.31**	**-0.12**
Adjusted R2	**0.82**	**0.81**	**0.85**	**0.93**	**0.89**	**0.93**	**0.91**	**0.90**	**0.88**	**0.77**	**0.03**
Annualized volatility	**18.8%**	**14.3%**	**13.4%**	**13.7%**	**14.4%**	**13.8%**	**15.5%**	**15.7%**	**17.8%**	**21.0%**	**14.0%**
Sharpe ratio	**0.72**	**0.93**	**0.90**	**0.85**	**0.94**	**0.79**	**0.68**	**0.87**	**0.72**	**0.65**	**0.01**

Decile performance of Morningstar's price/fair value estimates. Low value is the decile with highest price/fair values. High value is the decile with lowest P/FV. High-Low (H-L) is a portfolio which buys the high value decile and short sells the low value decile. The t-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

The returns and alphas are not very consistent within the deciles sorted on price/fair value. Both the higher and lower deciles contain annualized excess returns above 13%, and even though the alphas seem to be concentrated in the 5 most expensive deciles it is hard to paint a clear picture. The highest market alpha (3.7%) is found in the P2 decile and is barely significant with a t-value of 2.10. The stocks in this decile, on average, are significantly overvalued at an average price/fair value of 1.29. In general, we would expect the t-values to be less significant when we split our data sample into 10 relatively narrow percentiles.

This really shows that the reason for the sizeable alpha of the 1-star rated stocks is not solely due to them being expensive relative to Morningstar's fair value, but seemingly also stems from their uncertainty rating. The only difference between the star ratings and the price/fair value is the analyst's assessment of uncertainty, so if the raw price/fair value cannot explain the abnormal returns of the 1-star rating, perhaps the uncertainty ratings can. This would be consistent with the recent popularity asset pricing model (PAPM) stating that unpopular features, such as uncertainty and risk, demands a discount and for this reason yields abnormal returns (Kaplan et al., 2018, p. 9). We will leave it up to future research to test whether this is true.

Multiples and fundamentals of Morningstar's stock ratings

Table 4.33 investigates the past fundamental characteristics of the firms within Morningstar's various equity ratings and those stocks estimated to have a fair value higher than their price. We measure the key ratios in the most recent fiscal year, so these are historical fundamentals at the time of investment. Stocks with a higher rating had a clear tendency to also be more attractive based on fundamentals such as book-to-market, sales-to-market and FCFF/Enterprise value. The average book/market of 5-star rated stocks from 2003 to 2018 was 0.57 but only 0.29 for 1-star stocks. The free cash flow yield, or FCFF/EV, was 2.3% for 1-star stocks and the 5-star stocks had an impressive yield of 5.3%. Earnings yield was even negative (-3.2%) for the 1-star rated stocks meaning that, on average, the 1-star portfolio invests in companies with negative earnings. The 2-star stocks had a much lower sales/market (0.70) than any other rating, which seems curious, but we also note that the 1-star stocks are affected by outliers with large sales/market multiples. The 5-stars had the highest revenue relative to market cap (1.24) - as expected.

Looking at margins and returns on invested capital (ROIC), the 1-star stocks are clearly the least profitable, but the picture is less clear for the rest of the ratings. The 1-star stocks are not cheap or profitable, but they make up for it in revenue growth with an average of 10.6%. Otherwise, when moving from 2 to 5 stars, growth increases. The past growth of 5-star stocks (10.4%) is the second highest, but when we dive into the data, we observe that this high growth does not continue. If we instead look at the future growth (the growth in the same year as the ratings are given) 5-star stocks have the slowest growth (around 5%) while 1-star stocks have the fastest growth (around 9%). This could either explain why 5-star stocks appear cheap (the market correctly expects growth to slow), why 5-star stocks underperform (the growth slowdown disappoints the market), or both.

Table 4.33: Fundamental characteristics of Morningstar's ratings and price/fair value estimates

Morningstar portfolios Fundamentals	1 star	2 stars	3 stars	4 stars	5 stars	Morningstar P/FV
Book/Market	0.29	0.31	0.39	0.45	0.57	0.44
Sales/Market	1.01	0.70	1.04	1.07	1.24	1.05
FCFF/EV	2.3%	2.4%	3.1%	4.0%	5.3%	3.8%
EBITDA/EV	4.7%	8.0%	9.9%	11.9%	12.3%	11.5%
Earnings/Price	-3.2%	2.8%	3.9%	5.0%	5.7%	4.5%
ROIC	12.0%	19.2%	14.6%	15.6%	14.7%	12.9%
EBITDA margin	16.1%	23.0%	22.0%	23.9%	21.8%	22.8%
EBIT margin	8.0%	16.2%	15.5%	16.5%	15.7%	16.0%
1Y revenue growth	10.6%	6.7%	7.0%	8.8%	10.4%	8.4%
NIBD/Equity	0.34	0.60	0.71	0.44	-0.08	0.56

Illustrates the average historical fundamentals and key ratios of Morningstar's equity ratings and price/fair value estimates below 1. Enterprise value is market cap + net interest bearing debt (NIBD). We apply fundamentals from the last fiscal year with a 2-month lag.

Weighting: Equal weighted and monthly rebalancing.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Looking at the financial leverage of the star rated firms by measuring NIBD/equity shows that the 3-star stocks have the highest leverage (0.71) followed by the 2-star rating. We were surprised to see the highly volatile 1-star portfolio have relatively low debt, but this can be explained by the high exposure to tech-stocks that often carry a large amount of liquid reserves as opposed to debt - often resulting in negative NIBD in our sample.

On average, the 5-star stocks have no net interest bearing debt at all - in fact they have a slight negative NIBD on average, meaning that the firms have more cash and securities than debt. The latter is in line with previous indications that the 5-star rating favors firms with lower uncertainty ratings, since we would expect less indebted firms to carry less uncertainty. Yet, when looking at Morningstar's raw price/fair value estimates, which are not directly influenced by Morningstar's uncertainty rating as opposed to the star ratings, we still see a strong tendency for more undervalued stocks to have significantly lower NIBD relative to equity. The P/FV estimates are split into deciles in **Appendix 16** and underlines the same fundamental trends as in the star ratings - more undervalued firms have more attractive multiples and higher growth but are not necessarily more profitable.

Buying undervalued and shorting overvalued stocks

Here, we analyze a long/short portfolio based on Morningstar's price/fair value estimates, which is more comparable to the long/short portfolios based on the value driver formula and Gordon Growth in other sections. This portfolio buys the 30% most undervalued stocks and shorts the 30% most overvalued stocks. We also compare it to the 1 minus 5 stars portfolio and the H-L portfolio based on the 10% highest and lowest P/FV deciles. The portfolios are dollar neutral and equal weighted. The performance of these three portfolios are illustrated in **Appendix 17**.

Buying what Morningstar considers to be undervalued stocks while shorting the overvalued stocks have yielded negative annualized returns of -1.6% (the 30/30 portfolio) and -0.8% (H-L) in the 15-year period. When adjusting for common risk factors, the alpha of these portfolios become positive (but are still insignificant), due to their negative exposure (beta) towards the market. Although the portfolios are dollar-neutral, they are not exactly market-neutral - especially not the 1 minus 5 stars portfolio which still carries a market beta of 0.39. The information ratios are relatively unattractive (independent on which benchmark, we apply). Although the 1 minus 5 stars have impressive returns and alpha, it does not achieve an IR above 0.24 due to the high uncertainty, or tracking error, on its returns above the benchmark. The high tracking error means that the portfolio is more volatile and not very consistent in exceeding the benchmark. Still, betting against the star ratings have given an annualized excess return of 12.1%, which is formidable considering it is a long/short strategy.

4.4 Comparing the Investment Performance

This section outlines the similarities and differences between the investment portfolios based on Gordon Growth, the value driver model, and Morningstar's equity research.

The long-only portfolios of stocks with a price/fair value below 1 based on Gordon Growth and the value driver model have similar performance; they outperform their benchmarks significantly on raw returns and on a risk-adjusted basis. What Morningstar considers to be undervalued stocks have not outperformed the market and have been more volatile than both the benchmarks and most of our Gordon Growth and value driver portfolios. The stocks rated with 5 stars by Morningstar had the poorest returns, and the 4-star portfolio only performed slightly above average. On raw returns, the 1-star portfolio surprisingly beat everything else but did so with huge volatility.

When adjusting for common risk factors, the long-only Gordon Growth and value driver portfolios consistently maintain high abnormal returns (alpha) with market betas close to 1 and a small tilt towards the HML value factor. The long-only portfolios based on Morningstar's ratings and P/FV have materially lower alphas that are insignificantly different from zero. Morningstar's portfolio of undervalued stocks as well as the 4- and 5-stars surprisingly had a small tilt towards growth stocks (negative HML beta), but the 1-star had a much larger tilt towards growth. Only the 1-star portfolio maintained a high (but volatile) alpha, and a portfolio mixing 5- and 4-star stocks managed to reach a 4-factor alpha of 2.5% (t-stat = 1.95).

Comparing fundamentals

The fundamental multiples and key ratios across the P/FV deciles in the Gordon Growth and value driver model expose how different the strategies are. Although the undervalued stocks mostly trade at more attractive multiples, the value driver model have a lot more quality to it in terms of higher margins, ROIC and lower debt.

The Gordon Growth and value driver portfolios generally favored healthcare and consumer defensives while underweighting real estate and technology relative to the equal weighted S&P 500 excluding financials. The two formulas disagreed on energy stocks, as these were over-weighted by the value driver model and underweighted by Gordon Growth. We had expected the value driver model to better capture the value of fast growing companies due to the relationship between growth and investments in the formula, but we were surprised as one of the Gordon Growth models actually over-weighted the fast-growing technology sector, whereas the value driver models consistently underweighted tech. Morningstar was not a fan of technology either in the 15-year period, so many of the profitable tech-stocks landed in the 1-star portfolio. The 1-star portfolio also had an overweight in energy and instead underweighted consumer cyclicals, defensives, and industrials. Morningstar's analysts generally favored healthcare stocks with stable competitive advantages (moats) and low uncertainty ratings.

Comparing long/short performance

Looking at the High-Low (H-L) portfolios, Gordon Growth is robust and delivers strong performance across all portfolios, but half of the H-L value driver portfolios have considerably weaker performance. The H-L portfolios across the two models are similar regarding market beta - most of them are not completely market neutral, as the most undervalued stocks (the long side) are more correlated to the market than the most expensive stocks (the short side). The H-L portfolio based on Morningstar's P/FV has close to zero excess return and negative alpha.

The 30/30 long/short portfolios based on Gordon Growth and the value driver model have slightly lower returns and alpha compared to the H-L portfolios, but they also become less volatile (or consistent) in their outperformance which increases the statistical significance (t-values) and results in higher information ratios. Morningstar's 30/30 long/short portfolio is not an improvement upon the poor H-L performance. However, our abomination - the 1 minus 5 stars portfolio - delivers some of the highest excess and abnormal returns of any long/short strategy in our thesis. Yet, 1 minus 5 stars has huge volatility resulting in a poor information ratio and high market beta for a long/short strategy.

Stressing growth and WACC assumptions

We generally found the value driver models to be more robust towards changes in the underlying assumptions for steady-state growth. This is due to the dynamic in the value driver formula where there is a downside to higher growth; more investments. In the Gordon Growth models, a 3% higher growth directly translates into 3% higher free cash flows each year. In both models, higher growth results in more undervalued investment opportunities which reduces volatility by increasing diversification but also dilutes the abnormal returns (alpha). Lower growth generally leads to fewer undervalued investments but has an adverse effect on stocks with low returns on invested capital (ROIC) in the value driver model, as these benefit from slower growth. Despite stressing the assumptions to growth and WACC, most of our long-only and long/short portfolios continue to outperform their benchmark with higher returns, Sharpe ratios and positive alpha.

5 – Discussion

5.1 Model Construction

When constructing the different valuation strategies, we made several choices, which will be discussed in this section. We have pursued to rationalize all the choices by best practices from the literature and limit backtesting biases as much as possible.

The quantitative models have been constructed based on sound economic arguments rather than trying to optimize performance by fitting the variables (data mining). Instead, we present a total of 15 base valuation models and demonstrate robust performance across the board. We have pursued to test the impact of all modelling decisions throughout the thesis by stressing the assumptions of WACC, Growth, EBIT versus EBITDA, reported versus estimated FCFF etc.

The base models evaluate price/fair value based on the market cap at the closing price each month and invest at the same moment. In practice, it would not be possible to trade at the closing prices. This is one of the biases in our models. Yet, if we trade on the 1-month old price/fair values, the performance of the Gordon Growth models only diminishes marginally. Originally, Fama & French (1996, p. 61) found significant outperformance of the value factor even when lagging both financials and market capitalizations by 6 months. We have not tested whether our valuations are robust enough to outperform with a similar 6-month lag. It would depend on how fast market prices tend to mean-revert towards intrinsic value. Simultaneously, the effect of waiting before buying a stock that our models consider to be undervalued, does not necessarily have to be lower returns. If a stock appears undervalued because of negative price momentum, this could easily continue in the following months and impair our returns (Pedersen, Asness & Moskowitz, 2013). Thus, waiting for any negative momentum to disappear before buying an undervalued stock could also potentially improve returns.

For the most important variables in the valuation models, such as growth and WACC, we evaluate the impact on both performance and sector exposure in the analysis. Some might consider this to be data mining, but the rationale have not been to arrive at the best performance, but rather to give the reader full visibility of the impact of changing critical variables. In the base model we chose to apply a sector specific WACC based on a sample test from Morningstar and a fixed growth rate of 3.95%. Morningstar's sector specific WACC turns out to be considerably lower than the WACC measures from Bloomberg and Damodaran (NYU), which provides a bias towards certain sectors and higher valuations. The low WACC from Morningstar results in more undervalued investments - thus more diversified portfolios and lower volatility. This combined with a relatively high growth rate to perpetuity of 3.95% further increase this effect. However, since the numerator of the quantitative valuations is somewhat more conservative, as we exclude the explicit forecast period, there is a limit to the impact of changes in WACC and growth.

In the current environment of moderate growth and low inflation, it might seem aggressive to assume a long-term nominal growth rate of 3.95%. It is important to consider whether this high growth rate is reflected in the required return (WACC), since the spread between the two can otherwise become too narrow and result in unreasonably high valuations. The average WACC in our sector sample from Morningstar is 7.9%, the lowest is 6.4% (utilities), and the highest is 9% (technology). This makes the spread between growth and required return around 3.5% to 5%. As clarified in **Section 3**, the steady-state growth rate should not exceed the growth rate of the economy, and for this reason, one might argue that 3.95% is too high (Damodaran, 2015 p. 40).

An important detail to consider in terms of free cash flows is the impact from acquisitions. The S&P 500 companies often make both small and large acquisitions, and consolidation has been a particularly popular way of growing since the financial crisis. When a company acquires another, FCFF might take a dramatic hit due to the cash out flow - depending on how the acquisition is financed. This can potentially decrease the attractiveness of a company in our valuation models, as we do not adjust the past financials for acquisitions. FCFF consists of cash flows from operating activities and investing activities. The outflow of cash from the acquisition will negatively affect investing activities, and if the acquisition is financed by issuing debt, the new debt will increase the cash flow from financing activities (not included in FCFF). All else equal, the result is a lower FCFF and a higher net interest bearing debt - both of which affects our Gordon Growth valuations negatively. In particular, the LY FCFF model could be prone to suffer from this effect. The effect of acquisitions on the value driver models should be less pronounced, as NOPAT is not directly exposed to the large outflow of cash, although returns on invested capital (ROIC) could be affected materially as goodwill and invested capital increases (McKinsey, 2015, p. 112).

The valuations of the value driver models depend directly on ROIC, which makes it essential that the assumptions to both operating profits and invested capital are realistic. We include both goodwill and intangible assets as invested capital, but the result of excluding these items would be a higher ROIC and higher valuations. This would also increase exposure towards sectors with a lot of acquired goodwill and intangible assets as a result of M&A activity or R&D. Examples of sectors with high returns on invested capital excluding goodwill would be technology, healthcare, and consumer staples (McKinsey, 2015, p. 108).

The backtest period from April 2003 to September 2018 has been particularly favorable for U.S. stocks, and as a result, we find it important to discuss the consequences for our performance. Firstly, the period includes two economic expansions with two associated bull-markets, and the bull-market since 2009 has been one of the longest in history. The period only showcases one major downturn during the financial crisis and a few moderate setbacks in 2011 and 2015.

Secondly, the period does not include the Dot-com bubble that peaked in 2000, which potentially could impact the performance of our portfolios although most of them have not favored the relatively expensive technology sector. Yet, Morningstar's 1-star rating had a large overweight in technology stocks in our 15-year backtest. After we had performed the backtest, the U.S. stock market experienced large monthly drops both in October and December 2018, which were not included in our measurement period. These could have influenced our results - especially those of the long-only portfolios but would also have affected the benchmarks.

The measurement period is relatively short compared to the other empirical studies of risk-factors presented throughout this thesis. This especially impacts the level of statistical significance of our long/short strategies and decile portfolios, as many of the result have insignificant t-values. In terms of our long only strategies the results look somewhat better in terms of t-values. We usually generate t-values above 1.96 which are significant at the 95% level. We did not consistently find statistically significant long/short alphas above 1.96 (Pedersen, 2015, p. 29) and 3 (Harvey, Liu, and Zhu, 2015). However, both the level of alpha and t-values are generally slightly higher in the Gordon Growth models relative to the value driver models. We do not attribute the low t-values to a lack of performance in our backtest, but rather the short 15-year period. Statistical significance corresponds to realizing a high Sharpe ratio over a long period of time. Essentially, t-stat is approximately calculated as the Sharpe ratio multiplied by the square root of T (years) as described by Pedersen (2015, p. 53), so an otherwise attractive long/short Sharpe ratio of 0.40 would need roughly 60 years to achieve a t-stat of 3. As the Sharpe ratios are naturally higher on our long-only portfolios, this explains their higher t-stats.

It is best practice to test whether quantitative strategies work in other investment universes and markets over different time periods (Pedersen, 2015, p. 163). This increase the reliability of the backtest and probability of outperformance going forward. It has not been part of this project to test whether the strategies also worked on other markets in other periods of time, but it will definitely be something worth investigating in future research. We expect that when the strategy is implemented on broader markets with mid- and small-cap stocks as well, it will be positively affected by the size effect in line with other risk factors that also work better within small stocks (Alquist, Israel & Moskowitz, 2018, p. 8). Implementing the strategies on smaller stocks may also result in more losses from bankruptcies - especially for the Gordon Growth strategies, as they tend to favor firms with lower margins and higher financial leverage which indicates distress.

5.2 Quantitative Versus Qualitative Valuations

Whether recommendations of equity analysts out- or underperform is not a new topic. The subject has been studied empirically by a wide range of papers such as Bjerregaard-Nielsen, (2015), Barber, Lehavy, McNichols & Trueman (2001), and Desai, Liang & Singh (2000). Our analysis found that Morningstar's equity research did not confidently beat the benchmark or produce strong risk-adjusted abnormal returns. In fact, betting against Morningstar's recommendations resulted in high, but volatile, abnormal returns. We also found that the quantitative terminal value models consistently outperformed both Morningstar and the market. In this section, we discuss if and why quantitative beats discretionary.

Behavioral biases

Discretionary research and forecasts are made by analysts that can inherit several cognitive biases such as overconfidence, herding, recency bias, anchoring, conflicts of interest, and optimism (Bjerregaard-Nielsen, 2015). Interestingly, with Morningstar as an independent provider of equity research, conflicts of interest and incentive issues may be limited, as brokerage services and underwritings are not part of Morningstar's business (Bjerregaard-Nielsen, 2015, p. 7). Concerning optimism, the literature generally finds a large overweight of buy recommendations from equity analysts as opposed to sell and hold - especially for sell-side analysts. But from 2003 to 2018 only 26% of Morningstar's ratings were 4 or 5 stars (buy) whereas 25% were 1 or 2 stars (sell) for the S&P 500 stocks. In the heat of the financial crisis, however, the amount of 4- and 5-star opportunities spiked (see **Section 4.3**) and reached 55% compared to only 5% of 1- and 2-star ratings in total in September 2008 due to drastically low stock prices. In this context, we do not see any indication that Morningstar should be biased towards issuing buy-recommendations. But this does not imply that Morningstar's equity analysts cannot still be too optimistic or pessimistic in their valuations and earnings forecast.

Stotz (2016) shows that the consensus earnings forecasts of financial analysts are significantly biased towards optimism as they, on average, shoot 25% too high. The optimistic forecast error was particularly evident when companies experienced very low levels of actual earnings growth, and on the other hand, analysts typically underestimated the earnings of fast-growing firms. If we connect the accuracy of earnings forecasts to those of target prices or fair value, optimistic earnings projections could result in higher valuations and buy recommendations of stocks that ultimately underperform the market. In the opposite case, underestimating earnings growth of fast growing firms could result in a too low fair value estimate. In this context, it is fascinating that the revenue growth of 5-star stocks have been high historically but tend to slow down considerably after Morningstar's recommendations and provide disappointing returns. Simultaneously, 1-star stocks have high growth and very high returns. Although we do not have the data to back it up, we can only wonder if Morningstar's projections of earnings and cash flows might be too optimistic for 5-star stocks and too pessimistic for 1-star stocks.

Studies indicate that analysts have a bias towards herding (Desai, Liang & Singh, 2000), as their recommendations tend to align with those of other analysts, which in turn affects the performance of the recommendations. If a new 5-star stock is already considered undervalued by the consensus of analysts, the market might already have been aware and bought into the stock (thus raising the price and lowering its subsequent returns).

Data mining and biases in backtests

A systematic approach helps reduce a trader's own behavioral biases (Pedersen, 2015, p. 57), and since the quantitative valuations are based on realized historical financials - apart from our assumptions to WACC and growth - they are immune to most human biases. They are also ignorant to news flows and any guidance from the management of the firms being valued, which can be both an advantage and a disadvantage. On the one hand, having more information in a timely manner should give qualitative analysts an edge. On the other hand, we could argue that quarterly reporting and guidance may fixate markets on the short term, whereas our models are solely focused on estimating the long-term steady state. If the short-term trends of growth and margin improvements in a full-year guidance is extrapolated by analysts in their 5- or 10-year explicit forecasts, this may considerably affect not just the value in the explicit forecast period but also the terminal value which relies greatly on the fundamentals at the end of the forecast period (McKinsey, 2015, p. 250).

Applying an explicit forecast period (as most analysts do) or to exclude it (as our quantitative models do) can be valuable in some scenarios or prove unnecessary in other. Explicit forecast periods are necessary so the company can reach a steady-state level of growth and profitability before the analyst calculate the terminal value (McKinsey, 2015, p. 502). If a firm is already mature and has stable margins and low growth, we would argue there might not be a purpose for short-term forecasts, as these could likely exaggerate growth in accordance with the results of Stotz (2016). At the same time, we do experience that the undervalued and profitable investments identified by our quantitative models tend to be characterized by slower growth. The models have been less successful at systematically identifying and shorting overvalued stocks that provide negative alpha, and this could be because they simply lack the explicit forecast period necessary to correctly value immature and fast-growing stocks.

Quantitative models are exposed to several biases. Backtests typically look better than an actual trading strategy would in the real world because data mining and look-ahead bias can greatly influence results (Pedersen, 2015, p. 48). Although we have only applied past fundamentals from previous annual reports in the quantitative valuations, our assumptions for the cost of capital (WACC) are based on samples taken in 2018. We also apply an average growth rate of the U.S. economy measured from 2003 to 2017 to every valuation. The realized growth rate and Morningstar's WACC estimates of 2018 could not have been known back in 2003. Fortunately, the performance of our models is robust despite changes in our growth and WACC assumptions.

As the applied sector costs of capital depend directly on the estimates of Morningstar, Bloomberg or NYU Stern's Aswath Damodaran, this could present itself as a source of anchoring or herding, as our discount rates imitate those of other analysts. To accommodate this bias, and simultaneously improve the quantitative model's ability to differentiate WACC between firms in the same sector, one could estimate WACC quantitatively for each individual stock.

Can publicly available recommendations outperform in efficient markets?

A semi-strong form of market efficiency implies that investors should not be able to outperform by trading on publicly available information, such as analyst recommendations (Malkiel and Fama, 1970). The quantitative valuation models do have an advantage because the valuations are not public knowledge - although any investor can put last year's free cash flow in a Gordon Growth model. Popular multiples such as P/E and B/M, however, have been shown to outperform over time despite being publicly available.

Changes in target prices and recommendations are quickly absorbed and implemented in the stock prices, but quickly adjusting portfolios as soon as new recommendations are announced have been shown to outperform - but only before transaction costs (Barber, Lehavy, McNichols & Trueman, 2001). In this context, rebalancing portfolios daily to quickly account for any of Morningstar's rating changes sound like the necessary success criteria, as we only rebalance at the end of each month in the backtest. Apple could receive a 5-star rating on the 2nd of March, and our star portfolios would not know about it or adjust before the end of March. Much could happen with the stock price in the span of a month. Yet, a trading strategy or recommendation that relies on daily rebalancing is both costly and not very investor-friendly. Simultaneously, Morningstar does emphasize their long-term mindset and that market prices should converge on their fair value estimates within generally three years (Morningstar, 2015, p. 10). However, we did test whether daily rebalancing would change the overall performance of Morningstar's ratings. It did not.

Previous research by Morningstar suggests that the recommendations need more than a month to work their magic. When extending the holding period to 3 years, Morningstar finds that their ratings outperform on a wider sample of stocks (Collins & Gross, 2018). This implies forming monthly portfolios based on the star ratings and measuring the returns in up to 3 years after the portfolio formation. In other words, the 5-star rated stocks are bought and held for up to 3 years regardless of how their ratings change in these 3 years. We have performed the same exercise in our sample with both 1- and 3-year holding periods, but it was difficult to replicate the results of Collins & Gross.

Are valuations and fair value estimates the alpha and omega of equity research?

Although the quantitative valuations clearly outperform Morningstar's qualitative valuations in terms of risk and returns, equity research serves other purposes than just target prices and investment recommendations. Independent analysts can help investors, clients and managers to get to know the companies they invest in more intimately. Analysts often specialize in a group of firms in a certain industry or sector - thus acquiring in-depth knowledge of their markets. Simultaneously, they maintain close relationships to the management of the firms covered which puts them in a good position to receive first-hand information. Sophisticated or time-consuming research such as asking a vast number of third-party distributors how their sales have been of Apple's new iPhone can provide details about revenue expectations before the information is released to the public in a quarterly statement, which is valuable for any fundamentally driven investment strategy.

The quantitative valuations have a distinct weakness in the fact that they may result in negative fair values which are hard to interpret and difficult to trade on. If the stock does not have 10 years of accounting history, the valuation models based on 10-year fundamentals simply cannot provide an estimate. Simultaneously, the valuations are volatile and change considerably whenever they receive fresh data from the new annual reports. If the estimates and target prices of an equity analyst fluctuated wildly once a year, investors and clients would probably be skeptical.

Comparing quantitative terminal value and factor models

The quantitative terminal value models are not as efficient as other traditional factor models at splitting a universe of stocks into value versus growth, quality versus junk, or small versus big. In the eyes of the valuation-focused models, fast-growing technology stocks can be undervalued while stable and high-returning quality names can be expensive. As stated by Graham and Dodd (1934); "investments must always consider the *price* as well as the *quality* of the security." A fundamental valuation depends on a mix of parameters, that are difficult to capture in a single risk factor model; operating profit, growth, risk, returns on capital, debt, free cash flows, and more. But no matter how high the valuation, the price can be even higher. A stock is only attractive if it can be bought at a discount to its intrinsic value (Graham & Dodd, 1934).

Factor models based on simple metrics such as book/market, EV/EBITDA or free cash flow yield can be replicated faster and more easily, but the assumptions that an asset manager can make to differentiate his factor strategy are limited. The application of the quantitative terminal value models includes a variety of assumptions to WACC, steady-state growth, and the inputs based on the individual firm's fundamentals. By tweaking these inputs, the model can be tilted towards deep value, growth, quality, more diversification and lower risk, or certain sectors. This way, asset managers can differentiate their application of the terminal value models considerably to provide incremental value for their investors.

Much like the mispricing argument for the profitability and investment factors, often combined as the quality factor (Arnott, Harvey, Kalesnik & Linnainmaa, 2019, p. 30), we would argue that there is a similar explanation for the premium to undervalued stocks in the value driver model. The premium is a result of the undervalued stocks being conservative businesses with sustainable competitive advantages that maintain higher margins and profitability without high growth and large investments, which can hurt the balance sheet and drive up debt. The undervalued stocks stay out of the headlines and do not attract investors with a preference for "lottery-like payoffs" (Nguyen et al., 2014, p. 2). Such investors, and those who do not pay much attention to fundamentals, underpay and thus provide a premium for the undervalued stocks identified in the value driver models.

5.3 Benchmarks for Measuring Performance

Since the performance of our quantitative terminal value strategies is very strong in terms of Sharpe ratio and alpha - especially the long-only portfolios, this section will discuss the performance measures and benchmarks we use to measure this.

The long-only portfolios generate annualized single-factor alphas between 7% (10Y average NOPAT) and 3.5% (RONIC=WACC). One might think that these high levels are caused by only having one explanatory variable - the market - and that other well-known factors such as value and quality should explain most of our alpha. Yet, when we apply the HML and SMB as explanatory factors, the picture is not much changed – in fact, the 3-factor alphas are consistently higher than the single-factor alphas across our strategies. This might be explained by several factors e.g. portfolio weighting practice and investment universe - or that quantitative terminal value simply finds true alpha that cannot be explained by common risk factors.

Perhaps, adding more explanatory factors in the regressions will reduce the alphas. According to an article from AQR (one of the largest U.S. hedge funds), alpha is shrinking because more and more strategies become known and explain the otherwise "secret alphas" (Crowell, Israel, Kabiller & Berger, 2012). With the emergence of new beta, the unexplained alpha will naturally shrink and get reclassified as beta. AQR adjusts for 3 different types of beta (**Appendix 18**): Equity beta (which is the total stock market) Other market beta (markets such as commodities and real estate), and finally the hedge fund beta, which is other common factor strategies such as HML, SMB, Merger arbitrage, Momentum, Quality Minus Junk etc.

As explained in **Section 2**, we apply 3 different market benchmarks to represent the most precise equity beta, because our investment universe is not as broad as the global stock market. When evaluating performance, it is important that we compare to a benchmark with the best fit. As we only invest in the S&P 500 stocks excluding financials, a higher Sharpe ratio than the global market portfolio is not an impressive feat if it is still lower than the S&P 500 excluding financials. This benchmark, which is equal weighted and corresponds to our universe, had extraordinarily high Sharpe ratios from 2003 to 2018, but our long-only portfolios had even higher Sharpe ratios.

We have not applied any "Other market betas" because the returns we generate are solely in equity markets. Of hedge fund betas, our focus was on the Fama & French 3-factor model, which turned out not to limit the alpha. We also tried adding two more recently discovered factors, as we expected some of our returns to be explained by quality. The Robust Minus Weak (RMW), buys high profitability stocks and shorts low profitability stocks (Fama & French, 2015), while the Conservative Minus Aggressive (CMA) buys firms that invest conservatively and shorts the opposite (Fama & French, 2015). We would expect CMA to invest in firms with high cash flows just as our Gordon Growth models - thus explaining our returns. Simultaneously, our value driver models favor stocks with high profitability (ROIC), which should overlap with the RMW factor. Yet, when regressed on the 5-factor model, our abnormal returns did not diminish materially. This could be due to our investment universe, or that our portfolios are long-only and equal weighted instead of cap-weighted.

To really determine whether quantitative terminal value produces alpha in excess of the market and common sorts on size, value, profitability and investment, it would require that we construct equal weighted factor portfolios in our dataset and regress against these. An indication of the variables that potentially can explain the alpha of our strategies is found in the fundamentals we have calculated on a decile level, so we can examine specifically what characteristics, the stocks we invest in, have. The Gordon Growth strategies get more exposed to general value multiples such as free cash flow to enterprise value, Book to market and EBITDA to enterprise value, while the value driver model get more exposed to companies with higher profitability so have higher ROIC and margins but also to higher value multiples. Therefore, we would expect that explanatory variables such as HML or other value multiples to better explain the Gordon Growth performance, whereas Robust Minus Weak (Fama & French, 2015) or Quality Minus Junk (Pedersen, Frazzini, Asness, 2015) would better explain the alpha of the value driver model. However, by observing the factor loadings of the value driver models versus Gordon Growth, we find that both strategies have about equivalent HML beta, so value does explain some of our performance.

The value driver models are somewhat similar to Quality Minus Junk (QMJ) since they are dependent on the profitability due to NOPAT and ROIC, while highly leveraged firms receive lower valuations due to subtracting NIBD from the enterprise valuations. They also differ somewhat since the trading signal of QMJ does not depend on the price of a stock. This means that QMJ (Pedersen, Asness & Frazzini, 2015) risks buying too expensive quality stocks, which can impact performance. This means that the value driver models get exposure to both quality characteristics such as high profitability and low leverage but also to value multiples. Thus, the value driver models can be thought of as a combination of quality and value, which have proven to be a strong strategy (Pedersen, 2015 p. 104) known as GARP (Growth at a reasonable price) or QARP (Quality at a reasonable price).

A strategy that performs even better than combining quality and value is to combine both with momentum (Pedersen, 2015, p. 140). This makes it interesting to examine how the returns of our portfolios correlate with the Fama & French momentum (MOM) factor. When we calculate the correlations of both the long-only value driver and Gordon Growth models with momentum, we find negative correlations between -0.4 and -0.5. We also find negative correlations between our long/short portfolios and momentum. This presents an opportunity to combine these strategies with momentum and generate an even higher return with more diversification.

Since our investment universe is S&P 500, we probably have a unintended tilt towards quality companies since the largest U.S. stocks favor from a range of quality characteristics (Pedersen, 2013, p. 6). This also explains the high Sharpe ratio of our adjusted S&P 500 benchmark. Since our universe only includes large U.S. stocks, we do not benefit from any size effect, which also affects how well the various risk factors can explain our alpha. We would expect better performance if we implement our strategies on small-cap stocks, since we could benefit from the size effect (Fama & French, 1993, and Asness et al. (2015, p. 14).

Cliff Asness et al. (2015, p. 12) demonstrate how different value multiples such as Book/Market, Earnings/Price, and Cash Flow/Price have performed from 2001 to 2014. Book/Market experienced the lowest Sharpe ratio of 0.28, while Cash Flow/Price had a SR of 0.45. As these are long/short strategies, we compare them to our long/short portfolios. All Gordon Growth and value driver portfolios exhibit SR above 0.3 and most of them also beat 0.45.

Not all our long/short portfolios are equal in terms of performance. The long side of our portfolios perform similarly with high returns and Sharpe ratios, but the short side is not a consistently strong performer. This means that the quantitative terminal value is generally good at identifying undervalued stocks to buy, but only some of the quantitative valuation models are also good at identifying overvalued stocks to short. One of the reasons that the short side of the models are more challenged can be because expensive stocks have experienced tremendous growth and have kept being expensive throughout the period.

Since the financial crisis, value stocks have had a tough time while expensive growth, such as the FAANG stocks, have prospered. Momentum has also outperformed value (Pedersen, 2015, p. 138). Since the long/short portfolios have a positive beta exposure towards the HML value factor, they have had this trend against them. Investing in stocks trading at a low price/fair value resulted in attractive abnormal returns, but betting against the most overvalued stocks did not consistently contribute to our alpha. We can especially see this effect when we value-weight our portfolios.

We can also benchmark our portfolios against one of the great value investors, Warren Buffett. In the period 1984 to 2017, Buffett generated a Sharpe ratio around 0.62 (Pedersen, Kabiller & Frazzini, 2019, p. 27). This is certainly a longer time horizon very different from ours, but it tells us that the Sharpe ratios of our long-only strategies are in the high-end.

We have not implemented any optimization of rules for portfolio construction and diversification in our models, but we are aware of the valuable effects of especially diversification, which can optimize Sharpe ratios by lowering risk. According to Ilmanen & Villalon (2012), managers should focus much more on portfolio construction and cost control to generate higher risk-adjusted returns instead of just higher absolute returns. We could have implemented limits to the sector concentration in our portfolios or required a minimum number of stocks, but our portfolios appeared well diversified most of the time despite moderate sector tilts. Yet, even our most conservative valuation models managed to find at least 25 undervalued stocks or more every month. According to Statman (1987) around 30 stocks can make a portfolio diversified. However, if we increase the WACC applied in our models, some of them start to struggle finding enough undervalued stocks for a diversified portfolio.

5.4 With Great Returns Comes Great Drawdowns

"Cheap stocks must be risky or have low growth" (Pedersen et al., 2017, p. 3).

This section evaluates the previously mentioned portfolios with various alternative risk measures such as skewness, kurtosis, and drawdowns illustrated in **Appendix 19**. We discuss whether any abnormal returns are associated with higher risk and thus can be interpreted as risk premiums, or if they are in fact mispricing anomalies.

Skewness

As seen in **Appendix 19**, each of our tested long-only strategies have higher risk (standard deviations) than the market in the sample period. This is not only upside volatility but includes a tail risk with large drawdowns during economic turmoil as was the case in 2008 during the Financial Crisis and the sell-off in the summer of 2015. By applying alternative risk measures, this can also be expressed as negative skewness (asymmetric risk). The negative skewness essentially means that the portfolios tend to have many small gains and few large losses, which is also characterizes the stock market in general. The formula used for calculating skewness is written in **Appendix 21**.

A high negative skewness might explain the quantitative terminal value strategies' strong Sharpe ratios. In their 2014 paper, Nguyen et al. found that not only do most factors exhibit negative skew, but there appears to be a positive relationship between skewness and the factor's Sharpe ratio where more negatively skewed returns lead to higher Sharpe ratios. They suggest that the main determinant of risk premium is skewness and not volatility (Nguyen et al., 2014, p. 10).

In **Appendix 19**, our long-only Gordon Growth and value driver portfolios have negative skewness ranging from -0.69 (10Y Norm FCFF) to -0.36 (5Y Average NOPAT). The 10Y Average NOPAT and 10Y Average FCFF have a slight positive skewness because these two portfolios have a few large monthly gains above 15%. If we compare these levels of skewness to the Fama & French market's -0.76, our level of tail risk, does not seem inappropriately high. If we instead consider the skewness of our 30/30 long/short portfolios, these range between -0.03 (10Y Norm FCFF) and 2.21 (3Y Average NOPAT). According to Nguyen et al (2014, p. 10) most of our long/short portfolios seem to get the best of both worlds; attractive Sharpe ratios and positive skewness. On this basis, one could argue that our strategy of buying undervalued and selling overvalued stocks cannot meaningfully be classified as a risk premium but rather as a genuine market anomaly caused by mispricing, as they provide abnormal returns without abnormal risk (skewness). These results, in fact, compare to the positive skewness of HML, low volatility and trend following. We could argue, as Nguyen et al. (2014, p. 10) does for the HML value factor, that undervalued stocks are safe and defensive whereas undervalued stocks are a risky bet on future earnings. The most undervalued stocks provide a wider margin of safety between the stock price and its intrinsic value that could limit losses in case there are errors in the valuations.

Yet, Fama & French (1993) suggest that the abnormal return of HML is a risk premium for financial distress, and this is mostly in line with our results that undervalued stocks in the Gordon Growth models are less profitable and more leveraged than overvalued stocks. In extreme cases, our methodology can result in buying stocks on the brink of bankruptcy simply because their historical cash flows have been high - perhaps even because the firm is liquidating its assets.

Still, our models only operate within the S&P 500 index where the number of bankruptcies is minimal, and the constituents must live up to several criteria such as financial viability set forth by S&P Dow Jones Indices or they might be removed if their market cap becomes too small. As an example, RadioShack often appeared undervalued in our models during the 15-year period, but the stock was removed from the index long before it filed for bankruptcy in 2015. In this thesis, we cannot reject that the dynamic of only investing in S&P 500 stocks positively bias both our abnormal returns and risk considerably.

We found the long/short portfolios and undervalued stocks to hold up relatively well in 2008, where the stock markets suffered large losses, the U.S. economy was in recession, and the number of bankruptcies soared. It is difficult to argue that distressed firms should outperform in such an environment. The traditional HML value factor typically correlates negatively with the market, but during the financial crisis, the value factor correlated positively and considerably with the market - performing poorly as the markets tumbled and soaring as the stock markets rebounded (Arnott, Harvey, Kalesnik & Linnainmaa, 2019, p. 8). In our sample period, we find our long/short portfolios to be considerably less correlated with the market compared to the HML factor.

Kurtosis and drawdowns

Investors should not only dislike risks that exhibit negative skewness but also those with excess kurtosis (fat tails). A higher kurtosis indicates a higher probability of obtaining an extreme return, such as a month with very large negative or positive returns. The kurtosis of our long-only Gordon Growth and value driver portfolios are consistently not far from 3, which is the same level as a normal distribution - an attractive feature, as the most extreme return observations are limited. Their kurtosis is generally lower than for the S&P 500 adjusted for financials and duplicates, but they are higher than the more diversified Fama & French market portfolio. Their worst month returns are comparable or slightly lower than the S&P 500 adj. at around 19% but higher than the Fama & French market (17.2%).

Appendix 20 also illustrates the maximum drawdowns of the long-only portfolios as described in Lasse Pedersen's Efficiently Inefficient (2015, p. 39). The max drawdown is the cumulative loss since losses started (since the previous peak), and these are moderate compared to the S&P (48%) and market (51%) - especially for the more conservative of our long-only portfolios based on long term (5- and 10-year) average free cash flows and NOPAT.

Many of our long/short portfolios based on the value driver model have large excess kurtosis of up to 13.39, and this is not because the portfolios experience large negative returns, but because they exhibit very large positive returns in some months. The worst month's excess return in all the long/short portfolios range between -3.9% and -6.6%, which is not much compared to the market's -17.2% in October 2008 or HML with -11.1% in January 2009.

The maximum drawdowns of the long/short portfolios are mute at half the levels of the Fama & French value factor (HML) which indicates that the portfolios are well diversified and more defensive when markets tumble, or investor sentiment moves towards expensive stocks.

So why do the long/short value driver portfolios have such high kurtosis? The best months of our long/short portfolios yield double-digit returns of up to 17.9% - a massive number compared to the HML factor's 8.3% in its best month. On this area, however, we find a considerable difference between our models based on Gordon Growth and the value driver formula, as the best months of the Gordon Growth long/short portfolios yield returns between 6.6% and 13.7% - noticeably lower than the value driver models. This leads to considerably lower kurtosis for the Gordon Growth long/short portfolios.

The risk of missing out on the strongest month can affect an investor's return considerably in our portfolios, and unfortunately these months occur during the turmoil of the financial crisis, where many investors could be tempted to let go of their positions. Fortunately, our long/short portfolios consistently appear robust with lower monthly drawdowns compared to the HML factor. The formula used for calculating kurtosis and Drawdowns is written in **Appendix 21**.

Value traps

What about the risk of investing in so called "value traps"? These are defined by Pedersen, Asness & Frazzini (2013) as securities that appear cheap but deserve to be cheap. According to Penman & Reggiani (2018, p. 7), a stock with high earnings/price might not just have slow growth but can also be a company with high and risky growth - the stock appears cheap but might be a value trap. The valuations of our single-period terminal value models are, in our experience, inherently conservative, as they assume past financial performance of firms to continue in perpetuity. We have no explicit forecast period that acts as a runway for growth and profitability. Since our models do not assume high future growth or directly consider past growth, we find it less likely that our models will overvalue Penman & Reggiani's definition of a value trap. However, if some stocks appear undervalued due to their high risk and this is not fully reflected in our sector WACC assumptions or in the historical financials, this might present an implication.

In our long/short portfolios, we do not only run the risk of overvaluing value traps - we also risk undervaluing and shorting stocks that turn out to be great investments. The conservative nature of our valuations can result in large mispricings of stocks with low (or negative) free cash flows, operating earnings or returns on invested capital in the past. Some of these stocks might have attractive future prospects for growth or profitability that our models do not account for.

From the fundamental analysis of the long and short side of the portfolios, we know that the short side typically has higher historical growth, but in terms of other quality characteristics, the Gordon Growth and value driver models are miles apart. The stocks in the long side of the value driver models have higher margins, profitability and less debt, whereas the Gordon Growth models have lower margins, returns on capital, and higher debt, which smells like a value trap. Yet, Gordon Growth does not appear riskier in terms of volatility, drawdowns, or kurtosis - although they do have lower skewness than the long/short value driver models.

In short, the quantitative terminal value models might run into value traps or sell successful fast-growing firms that appear expensive with good reason, but in the past 15 years, the portfolios have been diversified enough to not suffer unreasonably large drawdowns and risks despite this fact.

Morningstar's ability to qualitatively evaluate risk bears fruit

With qualitative analysis, Morningstar can account for individual firm's risk in their WACC estimates and uncertainty ratings, and this should help avoid overvaluing risky firms. In their uncertainty rating, Morningstar accounts for operating and financial leverage, the predictability of sales, and the risk of a future event - such as product approval or legal decisions - impacting their valuation (Morningstar, 2015). Morningstar analysts also consider a bull- and bear-scenario in which the outcome of the company's fundamentals differ from their base case.

Yet, a long/short portfolio based on Morningstar's price/fair value estimates has higher volatility (9.2%) and relatively high beta (0.19). However, on metrics such as kurtosis, skewness and monthly drawdowns, Morningstar's long/short does appear more conservative. On the long-only portfolios based on Morningstar's ratings we also see some merit to the qualitative analysis of uncertainty. If we compare the 1-star stocks with 5-star stocks and 2-star stocks with 4-star stocks, higher star ratings have lower volatility, drawdowns, and kurtosis as well as negative skewness closer to zero. While Morningstar's stock ratings might not help you outperform the market significantly, they might help you to pick stocks with less risk.

The 1 minus 5 stars portfolio is simple to describe in terms of risk - it is extreme. If you had missed its greatest month, you would have missed a return of more than 100%, and the largest monthly loss was -20.7%. The max drawdown of -51% imitates that of a long-only portfolio.

The risk of betting against the market

The true risk of the terminal value-based portfolios is if the markets keep overvaluing expensive stocks and undervalue cheap stocks. This can result in extended periods of underperformance or stale returns in the portfolios based on quantitative terminal value. In the real world, we would have to pay margins on any short positions, and the margins grow if the positions move against us. As John Maynard Keynes would put it: “The market can stay irrational longer than you can remain solvent”, and therefore we emphasize the risk and potential drawdowns of the terminal value-based portfolios.

When expectations become unrealistic - at least compared to past fundamentals - our valuation models identify mispriced stocks that we either buy or short. If the market’s expectations do not materialize, the over- and undervalued stocks will have to mean revert at some point so that overvalued stocks underperform while undervalued stocks outperform (Siegel, 2014). Another risk is simply that the quantitative valuations might be wrong while the market is right. If the market’s expectations prove to hold water and undervalued stocks realize fundamentals that are materially weaker than their past levels, then our models should underperform. This is the risk of being a contrarian and betting against the market.

Since our models are focused on valuations, we would argue that the primary source of their abnormal returns are mispriced stocks due to irrationalities and behavioral aspects. On the one hand, mispricing is more likely to be arbitraged away and might not persist over time after their discovery (Asness, 2015, p. 2). On the other hand, if there is a risk-based explanation that demands a premium and results in the alphas of the terminal value models, one could argue that risk cannot be arbitraged away and that the abnormal returns should persist for this reason. For example, the market beta premium is well known but is not expected to disappear.

6 – Conclusion

The aim of this thesis was to explore if quantitative single-period valuations based on realized historical measures and without any explicit forecasts could beat the analyst-driven equity research of Morningstar at picking stocks within the S&P 500. We based our valuation models on the classic Gordon Growth formula, where free cash flows are assumed to grow at a constant rate, and the more sophisticated value driver model, where operating profitability and returns on invested capital are also considered. The goal was to determine the value of a stock based only on a calculation of terminal value.

When estimating terminal value, it is essential that inputs such as free cash flow, operating earnings, and returns on capital has reached a normalized steady-state level. The valuation models attempt to do this by applying both short- and long-term historical averages of these measures across business cycles. The base case models apply a constant growth rate of 3.95% and ten different sector costs of capital (WACC) based on sample tests from Morningstar's equity research. To test the robustness of the valuation models, we apply many different variations of growth, WACC, and company-specific inputs. The tests indicate that the performance is robust, but WACC greatly influences which sectors that appear most attractive. Simultaneously, too conservative assumptions regarding steady-state growth and WACC can reduce the amount of stocks that appear undervalued and make the investment strategies more concentrated and riskier.

We benchmarked the valuation models and Morningstar's recommendations against the Fama & French market portfolio, the S&P 500 index, and the equal weighted S&P 500 excluding financials. We also compared our performance to the results obtained in other studies of quantitative factors and equity risk premiums. The 15-year backtest from April 2003 to September 2018 has been a relatively profitable period to be exposed to the S&P 500, and the benchmarks sustained average Sharpe ratios around 0.86. This naturally gives the performance of our models some tailwind too.

We tested 15 base versions of the single-period valuation models, and they have consistently outperformed Morningstars recommendations and relevant market benchmarks. Simply buying every stock trading below our estimates of intrinsic value generates significant annualized alphas of 3.5% or more and strong Sharpe ratios of around 0.9. We find the strongest performance within the most conservative valuation models based on 3-, 5-, and 10-year average NOPAT or FCFF. Implicitly, these models favor stocks with slow or negative growth in free cash flows and operating profits.

The Gordon Growth models applying a normalized EBITDA to FCFF ratio have relatively weaker performance. The same can be said for the value driver models that apply a median ROIC to the most recent year's NOPAT or assumes steady-state RONIC to equal the sector WACC - they are less robust and have weaker performance but still beat their benchmark. When dividing all stocks into price/fair value deciles, the returns, Sharpe ratios, and alphas increase going from the most overvalued stocks to the most undervalued stocks. Cheap stocks also tend to have higher market exposure (beta) - indicating that a part of their higher returns is a compensation for taking more systematic risk.

To better understand which companies that appear undervalued in the quantitative terminal value models, we have identified which sectors they have a higher or lower exposure towards compared to the S&P 500 excluding financials. It proves that the sector exposure of our strategies is closely related to the applied WACC. The base models with Morningstar's WACC overweight healthcare and consumer defensive, but when we apply different WACC measures, the strategies abandon healthcare stocks and instead overweight technology and consumer cyclicals. Because the single-period valuations are relatively conservative, applying too high WACC will result in much fewer undervalued stocks, which hurts the diversification of the portfolios and increases volatility.

When looking at the fundamental multiples and key ratios of the stocks that appeared undervalued in the Gordon Growth and value driver models, we identified a major difference. Although the undervalued stocks in both models mostly trade at more attractive multiples such as Earnings/Price and Book/Market, the value driver models clearly favor quality firms with higher margins, ROIC and lower debt, whereas Gordon Growth favors firms that are less profitable and have higher debt.

Morningstar's recommendations did not perform as we had expected in the 15-year period. 5-star stocks had the lowest monthly returns while 1-star stocks had the highest - both exhibited high volatility and market exposure. The lowest risk-adjusted returns (Sharpe ratio) were achieved by the 5 star-stocks (0.47) and the highest by the 3-star stocks (0.79). A portfolio of both 4- and 5-star rated stocks did slightly better and generated a 4-factor alpha of 2.5% (t-stat = 1.95) but was still only roughly on par with the S&P 500 excluding financials. The performance of the 1- and 5-star portfolios was influenced by the fact that not many stocks were given these ratings, which makes the results less robust.

When measuring the performance of buying the 30% most undervalued stocks and short selling the 30% most overvalued stocks in the quantitative terminal value models, they produce considerable abnormal returns (alpha) in most of our portfolios and consistently beat the Fama & French HML value factor. However, the long/short performance is generally less robust - especially in the value driver models - which indicates that the quantitative terminal value models are better at identifying undervalued stocks that outperform rather than finding expensive stocks to short. However, some of the long/short portfolios were considerably better than others. These were 3Y Average FCFF (SR: 0.77), LY FCFF (SR: 0.70), and 10Y average NOPAT (SR: 0.65). The short-side performs particularly poor when we value-weight the Gordon Growth portfolios, as it has not been a good idea to short large and expensive stocks in the S&P 500 the past 15 years.

We have aimed to remove as many biases from the results as possible and have been evaluating the data several times to optimize data quality as much as possible. We can conclude that the strategies have proven strong from April 2003 to September 2018 within the S&P 500 excluding financials. We naturally cannot conclude that this performance will be as solid in the future or on other equity markets during other time periods, but this would be an interesting subject for future research.

7 – References

Abrams, J, (2000): Quantitative Business Valuation: A Mathematical Approach for Today's Professionals, second edition, Irwin library.

Andersen, I. (2013): Den skinbarlige virkelighed, Samfundslitteratur

Alquist R., Israel R. & Moskowitz T. (2018): Fast, Fiction, and the Size Effect, The Journal of Portfolio Management, Vol. 45(1). https://www.aqr.com/Insights/Research/Journal-Article/Fact-Fiction-and-the-Size-Effect

Arnott R., Harvey C., Kalesnik V. & Linnainmaa J. T. (2019): Alice's Adventures in Factorland: Three Blunders That Plague Factor Investing. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3331680

Asness, C. (1994): Variables that explain stock returns, Ph.D. Dissertation, University of Chicago.

Asness, C. (2015): How Can a Strategy Still Work If Everyone Knows About It? https://www.aqr.com/Insights/Perspectives/How-Can-a-Strategy-Still-Work-If-Everyone-Knows-About-It

Armstrong, C,. Hand, T., Davilla, G. & Foster, J. (2011): Market-to-revenue multiples in public and private capital markets, Australian Journal of Management, Vol. 36. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1830580

Barber B., Lehavy R., McNichols M. & Trueman B. (2001): Can Investors Profit From The Prophets? Security Analyst Recommendations and Stock Returns, The Journal of Finance, Vol. 56(2), page 531-563.

Bolster J. & Trahan A. (2013): Investing in Morningstar Five-Star Stock Upgrades: Price and Style Effects, The Journal of Accounting and Finance, Vol. 13(6), page 193-208. http://m.www.na-businesspress.com/JAF/TrahanEA_Web13_6_.pdf

Bowerman, B., O'Connel, R. & Koehler, A. (2005): Forecasting, Time series and regression. Fourth Edition. Duxbury applier series.

Callahan D. & Mauboussin M., (2014): Calculating Return on Invested Capital, Credit Suisse https://plus.credit-suisse.com/rpc4/ravDocView?docid=P8BJ3Y

Chen N. & Zhang F. (1998): Risk and Return of Value Stocks, The Journal of Business, Vol. 71(4), page 501-535. https://www.jstor.org/stable/10.1086/209755

Cochrane, J. (2000): Asset pricing, Chicago Booth.

Collins E., Gross C. & Morningstar Inc. (2018): Analyzing the Performance of Our Stock Recommendations. morningstar.com/articles/859628/analyzing-the-performance-of-our-stock-recommendat.html

Cooper, I. (2016): Estimating sustainable normalized operating free cash flow, London Business School.

Cowen, B., Israel, C., Kabiller, G. & Berger, A. (2012): Is Alpha Just Beta Waiting To Be Discovered, AQR. https://pdfs.semanticscholar.org/9db3/822c3a56c8958a37b6d2111d90f4d6ff9300.pdf

Cowen, A., Groysberg, B. & Healy, P. (2006). Which types of analyst firms are more optimistic? Journal of Accounting and Economics 41, pp. 119–146.

Damodaran, A. (2019): Cost of capital by sector, New York University - Stern. http://people.stern.nyu.edu/adamodar/New_Home_Page/datafile/wacc.htm

Damodaran, A. (2002): Investment valuation - Second edition, Wiley Finance.

Damodaran, A. (2018): Cost of Capital, New York University - Stern.
http://pages.stern.nyu.edu/~adamodar/New_Home_Page/datacurrent.html

Damodaran, A. (2015): Growth rates and Terminal value, New York University - Stern.
http://people.stern.nyu.edu/adamodar/pdfiles/ovhds/dam2ed/growthandtermvalue.pdf

Desai H., Liang B. & Singh A. K. (2000): Do All-Stars Shine? Evaluation of Analyst Recommendations, Financial Analysts Journal, Vol. 56(3), p. 20-29.

Fama, E. & French, K. (2015). A five-factor asset pricing model, Journal of Financial Economics.
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2287202

Fama, E. & French, K. (1992a). The Cross-Section of Expected Stock Returns. The Journal of Finance 47(2), pp. 427-465.

Fama, E. & French, K. (1992b). The Economic Fundamentals of Size and Book-to-Market Equity, working paper. Chicago, Illinois: Graduate School of Business, University of Chicago.

Fama, E. & French, K. (1993): Common Risk Factors in the Returns on Stocks and Bonds. Journal of Financial Economics 33, pp. 3-56.

Fama, E. & French, K. (1996): Multifactor explanations of asset pricing anomalies, The Journal of Finance Vol. LI, NO. 1.

Federal Reserve Bank of St. Louis, FRED research (2018)**:**
http://research.stlouisfed.org/fred2/data/gdpc1rm.txt
https://fred.stlouisfed.org/data/PCECTPICTM.txt

Francis, J., Olsson, P. & Oswald D. (2000): Comparing the accuracy and explainability of dividend, free cash flow and abnormal earnings equity value estimates. Journal of Accounting Research 38

Frankel, R. & Lee, C. (1998): Accounting valuation, market expectation, and cross-sectional stock returns. Journal of Accounting and Economics 25

French, K. (2018): http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research

Gebhardt, W., & Swaminathan, B. (2001): Toward and ex ante cost-of-capital.Journal of Accounting Research

Gordon, M. (1962): The review of Economics and Statistics, MIT press Vol 44, No 1.

Grey, W. & Vogel, J. (2012): A Performance Horse-Race over the past 40 Years, The Journal of portfolio management. http://csinvesting.org/wp-content/uploads/2012/09/tev-to-ebitda-research.pdf

Guba, E. (1990): The Paradigm Dialog, SAGE publications.

Hedayati, S., Hurst, B. & Stamelos, E. (2018): Transaction Costs: Practical Application, AQR. https://www.aqr.com/Insights/Research/White-Papers/Transactions-Costs-Practical-Application

Heldbjerg, G. (1997): Grøftegravning i metodisk perspektiv, Samfundslitteratur.

Harvey C., Liu Y. & Zhu H. (2016): … and the Cross-Section of Expected Returns, The Review of Financial Studies, 2016, Vol. 29(1), page 5-68, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2249314

Ilmanen, A. & Villalon, D (2012): Alpha beyond expected return, AQR.
https://www.aqr.com/Insights/Research/White-Papers/Alpha-Beyond-Expected-Returns

Johnson, P., Lopez, T. & Sanchez, J. (2011): Special Items: A Descriptive Analysis, Accounting Horizons Vol. 25(3), page 511-536.

Kaplan, S. & Ruback, R. (1995): The valuation of cash flow forecasts: an empirical analysis, Journal of Finance 50.

Levine, C., Das, S. & Sivaramakrishnan, K. (1998). Earnings predictability and bias in analysts' earnings forecasts. The Accounting Review 73, pp. 277-294.

Lundholm, R. & O'Keefe, T. (2001): Reconciling Value Estimates from the Discounted Cash Flow Model and the Residual Income Model

Mauboussin M. & Johnson P. (1997): Efficient Capital Markets: A Review of Theory and Empirical Work, Journal of Finance Vol. 25(2), page 383-417.

Malkiel B. & Fama E. (1970): Competitive Advantage Period: The Neglected Value Driver, Financial Management Vol. 26(2), page 67-74.

Meitner, M. (2013): Multi-period Asset Lifetimes and Accounting-based Equity Valuation: Take Care with Constant-growth Terminal Value Models!

McKinsey & Company, Koller, T., Goedhart, M. & Wessels, D. (2015): Valuation – Measuring and Managing the Value of Companies, 6th edition.

Morningstar inc. (2015): Equity Research Methodology, http://corporate1.morningstar.com/WorkArea/DownloadAsset.aspx?id=11725.

Morningstar inc. (2017): Year of Valuation Analyst Handbook.

Myers, S., & Turnbull, S. (1977): Capital Budgeting and the Capital Asset Pricing Model: Good News and Bad News, The Journal of Finance.

Myron J. Gordon (1962): The investment and valuation of a corporation, Homewood.

National Bureau of Economic Research (2019): https://www.nber.org/cycles.html

Newbold, P., Carlson, W. & Thorne, B. (2013): Statistics for business and economics, Pearson.

Nissim, D. (2017): Terminal Value, Columbia Business School.

Nissim, D. (2017a): EBITDA, EBITA or EBIT, Columbia Business School

Northern Trust (2018): The Value Factor Isn't Dead, Just Misapplied, https://pointofview.northerntrust.com/the-value-factor-isnt-dead-just-misapplied-224dde2049f2

Pedersen, L. (2015): Efficiently Inefficient: how smart money invests and market prices are determined, Princeton University Press.

Pedersen L., Asness C. & Frazzini A. (2013): Quality Minus Junk, working paper. http://www.econ.yale.edu/~shiller/behfin/2013_04-10/asness-frazzini-pedersen.pdf

Pedersen L., Frazzini A. & Kabiller D. (2018): Buffett's Alpha, Financial Analysts Journal Vol. 74(4), p. 35-55. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3197185

Pedersen L., Asness C., Liew J. & Thapar A. (2017): Deep Value, working paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3076181

Pedersen, L., Asness, C. & Moskowitz, T. (2013): Value and momentum everywhere. Chicago booth.

Pedersen L. & Frazzini A. (2013): Betting against beta, NYU Stern. http://pages.stern.nyu.edu/~lpederse/papers/BettingAgainstBeta.pdf

Penman, S. (1998): A comparison of dividend, cash flow, and earnings approaches to equity valuation. Contemporary Accounting Research.

Petersen, C., Plenborg, T. & Kinserdal, F. (2017): Financial statement analysis, Fagbokforlaget.

Platt, D., Demirkan, S. & Platt, M. (2009): Perilous Forecasts: Implications of Reliance on Terminal Value, *https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1397711*.

Reichart, K. (2009): Is Your Manager Trading Too Much? https://www.morningstar.com/articles/304376/is-your-manager-trading-too-much.html

Rekenthaler, J. (2018): Den rigeste procent - aktieudgaven.
http://www.morningstar.dk/dk/news/169959/den-rigeste-procent---aktieudgaven.aspx

Saunders, M., Lewis, P. & Thornhill, A. (2012): Research Methods for Business Students, Pearson, 6th edition.

Sharpe, W. (1964): Capital asset prices: A Theory of Market Equilibrium under Conditions of Risk

Sharpe, W. (1995): Risk, Market Sensitivity, and Diversification, Financial Analysts Journal, Vol. 51(1), page 84-88.

Siegel, J. (2014): Stocks for the long run.

Statman, M., (1987): How Many Stocks Make a Diversified Portfolio, Journal of Financial and Quantitative Analysis.

Stotz, A. (2016): An Empirical Study of Financial Analysts Earnings Forecast Accuracy, https://ssrn.com/abstract=2943146

Sørensen, O. (2012): Regnskabsanalyse og værdiansættelse - en praktisk tilgang, 4th edition, Gjellerup/Gads Forlag, København K.

The balance (2018): https://www.thebalance.com/us-gdp-by-year-3305543

The world bank (2018):
data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=US&name_desc=true

U. S. department of treasury (2018):
https://www.treasury.gov/resource-center/data-chart-center/interest-rates/pages/textview.aspx?data=yield

U.S. Securities and Exchange Commission (18-01-2019): Form 10-K. Retrieved from https://www.sec.gov/fast-answers/answers-form10khtm.html

8 – Appendix

Appendix 1 - Three Types of Quantitative Investing

	Fundamental quantitative investing	**Statistical arbitrage**	**High-Frequency trading**
Based on	Economics, finance & statistics	Arbitrage relations, statistics	Statistics, engineering, information processing
Turnover	Day to months	Hours to days	Instances to hours
Capacity	Higher	In between	Lower
Who determines trade	Strategy	Strategy, but some orders may not be filled	Market
Backtest	Reliable	Transaction-cost estimate essential	Heisenberg uncertainty principle of finance

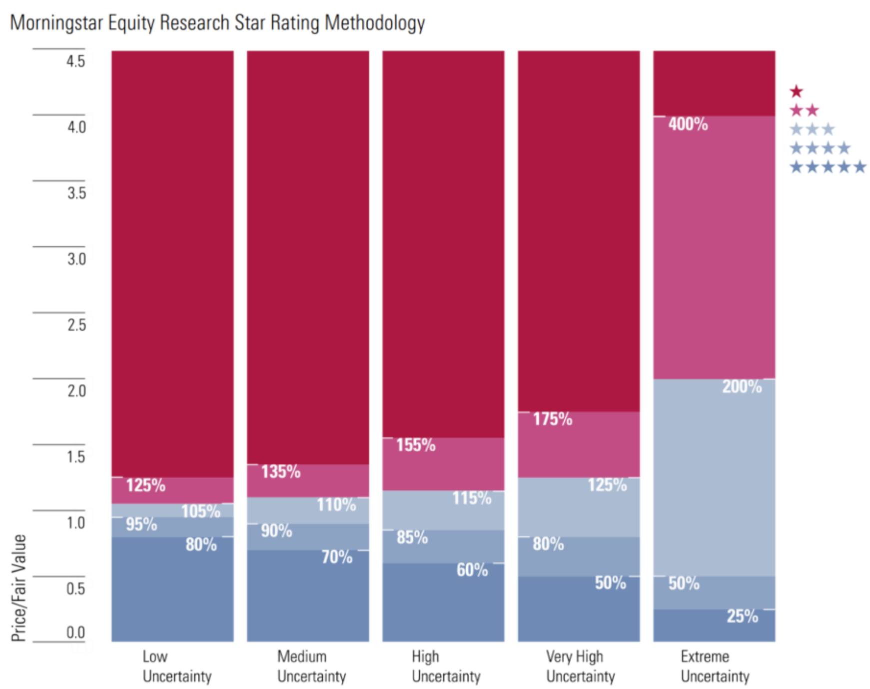
Three types of quantitative investing

Source: Pedersen, 2015, P.134

Appendix 2 - Morningstar Uncertainty Rating

The uncertainty ratings for the qualitative analysis are low, medium, high, very high, and extreme.

- Low: Margin of safety for 5-star rating is a 20% discount and for 1-star rating is a 25% premium.
- Medium: Margin of safety for 5-star rating is a 30% discount and for 1-star rating is a 35% premium.
- High: Margin of safety for 5-star rating is a 40% discount and for 1-star rating is a 55% premium.
- Very high: Margin of safety for 5-star rating is a 50% discount and for 1-star rating is a 75% premium.
- Extreme: Margin of safety for 5-star rating is a 75% discount and for 1-star rating is a 300% premium.



Source: Morningstar Rating for Stocks - Analyzing the performance of our stock recommendations (2018, p. 36).

Appendix 3 - Estimated FCFF Applied in the Gordon Growth Models

	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.
Ann. Excess return	14,83%	14,32%	13,04%	13,13%	15,42%	16,02%	15,05%
Ann. volatility	15,10%	15,07%	14,34%	13,82%	15,23%	15,09%	15,74%
Sharpe ratio	0,98	0,95	0,91	0,95	1,01	1,06	0,96
Cumulative return	9,88	9,15	7,64	7,83	10,79	11,87	10,09
Decile portfolios H-L	**LY FCFF H-L**	**3Y Norm H-L**	**5Y Norm H-L**	**10Y Norm H-L**	**3Y avg. H-L**	**5Y avg. H-L**	**10Y avg. H-L**
Ann. Excess return	**10,83%**	**6,42%**	**3,87%**	**1,77%**	**12,21%**	**13,86%**	**5,93%**
t-values	2,85	2,48	1,54	0,66	2,66	3,17	1,62
Alpha (MKT)	**8,12%**	**8,12%**	**4,37%**	**3,36%**	**2,72%**	**9,53%**	**12,07%**
t-values	2,14	1,70	1,31	0,99	2,07	2,71	0,07
Alpha (S&P 500)	**8,20%**	**4,41%**	**3,28%**	**2,61%**	**9,60%**	**12,12%**	**7,21%**
t-values	2,16	1,72	1,28	0,95	2,08	2,73	0,61
Alpha (S&P 500 adj.)	**6,63%**	**3,57%**	**3,11%**	**2,62%**	**7,37%**	**10,24%**	**0,27%**
t-values	1,79	1,41	1,20	0,95	1,64	2,34	0,08
3-factor alpha (MKT)	**9,15%**	**5,17%**	**4,14%**	**3,47%**	**10,75%**	**13,15%**	**3,14%**
t-values	2,57	2,20	1,73	1,34	2,50	3,13	1,00
3-factor alpha (S&P 500 adj.)	**8,02%**	**4,63%**	**3,90%**	**3,24%**	**9,01%**	**11,65%**	**1,93%**
t-values	2,30	2,00	1,63	1,25	2,14	2,80	0,64
Beta (MKT)	**0,26**	**0,20**	**0,05**	**-0,09**	**0,26**	**0,17**	**0,26**
t-values	3,33	3,71	0,92	1,61	2,70	1,88	0,18
Beta (S&P 500)	**0,27**	**0,21**	**0,06**	**-0,09**	**0,27**	**0,18**	**0,39**
t-values	3,33	3,74	1,10	1,47	2,71	1,88	5,14
Beta (S&P 500 adj.)	**0,34**	**0,23**	**0,06**	**-0,07**	**0,39**	**0,29**	**0,45**
t-values	4,70	4,67	1,22	-1,28	4,48	3,44	6,99
Information ratio (MKT)	**0,56**	**0,44**	**0,34**	**0,26**	**0,54**	**0,71**	**0,15**
Information ratio (S&P 500)	**0,56**	**0,45**	**0,33**	**0,25**	**0,54**	**0,71**	**0,53**
Information ratio (S&P 500 adj.)	**0,47**	**0,37**	**0,32**	**0,25**	**0,43**	**0,61**	**0,02**
Adj. R^2	**0,18**	**0,23**	**0,15**	**0,14**	**0,18**	**0,14**	**0,33**
Sharpe ratio	**0,72**	**0,63**	**0,39**	**0,17**	**0,68**	**0,80**	**0,41**

Quartile H-L	LY FCFF H-L	3Y Norm H-L	5Y Norm H-L	10Y Norm H-L	3Y avg. H-L	5Y avg. H-L	10Y avg. H-L
Excess annualized return	**7,85%**	**5,70%**	**3,81%**	**1,66%**	**7,02%**	**6,88%**	**3,63%**
t-values	3,28	2,79	2,24	0,86	2,80	3,01	1,74
Alpha (MKT)	**6,43%**	**4,74%**	**3,93%**	**2,76%**	**6,28%**	**6,51%**	**2,91%**
t-values	2,67	2,23	2,25	1,42	2,45	2,78	0,04
Alpha (S&P 500)	**6,48%**	**4,72%**	**3,84%**	**2,59%**	**6,27%**	**6,48%**	**3,79%**
t-values	2,68	2,22	2,21	1,32	2,47	2,79	1,36
Alpha (S&P 500 adj.)	**5,35%**	**4,07%**	**3,75%**	**2,67%**	**5,18%**	**5,66%**	**2,25%**
t-values	2,28	1,93	2,13	1,36	2,05	2,43	1,06
3-factor alpha (MKT)	**7,09%**	**5,42%**	**4,51%**	**3,36%**	**7,10%**	**7,24%**	**3,70%**
t-values	3,15	2,79	2,83	1,88	3,07	3,39	1,97
3-factor alpha (S&P 500 adj.)	**6,95%**	**5,08%**	**3,40%**	**1,71%**	**6,23%**	**6,13%**	**2,63%**
t-values	2,81	2,53	2,66	1,70	2,67	3,03	1,67
Beta (MKT)	**0,14**	**0,09**	**-0,01**	**-0,11**	**0,07**	**0,04**	**0,07**
t-values	2,74	2,10	-0,34	-2,64	1,35	0,73	1,58
Beta (S&P 500)	**0,14**	**0,10**	**0,00**	**-0,10**	**0,08**	**0,04**	**0,08**
t-values	2,74	2,20	-0,08	-2,29	1,41	0,82	1,72
Beta (S&P 500 adj.)	**0,20**	**0,13**	**0,00**	**-0,08**	**0,15**	**0,10**	**0,11**
t-values	4,42	3,22	0,00	-2,14	3,03	2,18	2,71
Information ratio (MKT)	**0,70**	**0,58**	**0,59**	**0,37**	**0,64**	**0,73**	**0,36**
Information ratio (S&P 500)	**0,70**	**0,58**	**0,57**	**0,35**	**0,64**	**0,72**	**0,46**
Information ratio (S&P 500 adj.)	**0,60**	**0,51**	**0,56**	**0,36**	**0,54**	**0,64**	**0,28**
Adj. R^2	**0,17**	**0,20**	**0,18**	**0,20**	**0,21**	**0,19**	**0,25**
Sharpe ratio	**0,83**	**0,69**	**0,57**	**0,22**	**0,71**	**0,76**	**0,44**

Performance measures for Gordon's growth strategies with estimated FCFF applied instead of reported.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Market & Period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 4 - WACC Stress Sector Distribution for Gordon Growth

Damodaran (NYU) WACC

	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.	S&P 500 adj.
Technology	21%	23%	25%	26%	23%	25%	27%	17%
Consumer Cyclical	25%	28%	30%	34%	30%	32%	38%	18%
Healthcare	9%	7%	6%	6%	7%	7%	6%	13%
Energy	6%	5%	3%	5%	4%	4%	3%	8%
Communication Services	4%	5%	5%	3%	4%	3%	1%	3%
Consumer Defensive	8%	7%	6%	5%	6%	7%	6%	9%
Industrials	14%	14%	14%	14%	13%	12%	11%	14%
Basic Materials	5%	5%	5%	4%	5%	5%	5%	6%
Utilities	6%	5%	5%	4%	6%	4%	1%	6%
Real Estate	2%	2%	2%	0%	2%	1%	2%	5%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Bloomberg WACC

	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.	S&P 500 adj.
Technology	15%	14%	14%	14%	15%	16%	16%	17%
Consumer Cyclical	23%	24%	24%	25%	25%	26%	30%	18%
Healthcare	7%	5%	5%	4%	5%	5%	4%	13%
Energy	6%	5%	4%	4%	5%	5%	4%	8%
Communication Services	3%	3%	3%	2%	3%	2%	1%	3%
Consumer Defensive	16%	18%	18%	19%	16%	16%	15%	9%
Industrials	12%	11%	11%	11%	10%	9%	8%	14%
Basic Materials	6%	6%	6%	6%	6%	5%	5%	6%
Utilities	9%	10%	11%	13%	11%	13%	15%	6%
Real Estate	3%	3%	3%	2%	3%	3%	2%	5%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Morningstar sample WACC

	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.	S&P 500 adj.
Technology	15%	15%	14%	14%	16%	17%	19%	17%
Consumer Cyclical	18%	19%	18%	18%	19%	20%	23%	18%
Healthcare	15%	15%	15%	17%	14%	15%	16%	13%
Energy	6%	5%	5%	4%	6%	5%	5%	8%
Communication Services	3%	3%	3%	3%	3%	3%	1%	3%
Consumer Defensive	14%	16%	16%	17%	15%	15%	15%	9%
Industrials	15%	15%	15%	15%	14%	13%	11%	14%
Basic Materials	6%	6%	6%	6%	6%	6%	5%	6%
Utilities	5%	5%	5%	5%	5%	6%	4%	6%
Real Estate	2%	2%	2%	1%	2%	2%	1%	5%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Equal sector WACC (9%)								
	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.	S&P 500
Technology	19%	20%	22%	23%	22%	24%	28%	17%
Consumer Cyclical	22%	23%	23%	25%	24%	27%	31%	18%
Healthcare	12%	10%	10%	11%	9%	9%	8%	13%
Energy	6%	6%	6%	7%	6%	6%	5%	8%
Communication Services	3%	4%	4%	3%	3%	3%	1%	3%
Consumer Defensive	10%	10%	10%	8%	9%	8%	7%	9%
Industrials	16%	16%	16%	15%	15%	14%	12%	14%
Basic Materials	7%	7%	7%	7%	7%	6%	6%	6%
Utilities	3%	2%	2%	1%	3%	1%	0%	6%
Real Estate	2%	2%	1%	1%	1%	1%	1%	5%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Sector exposure for Gordon's growth strategies with different WACC estimates applied.
The greener the color is of the cell the bigger the number is compared to the other percentages

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples., Bloomberg, Damodaran (NYU), 9%.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Market & Period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

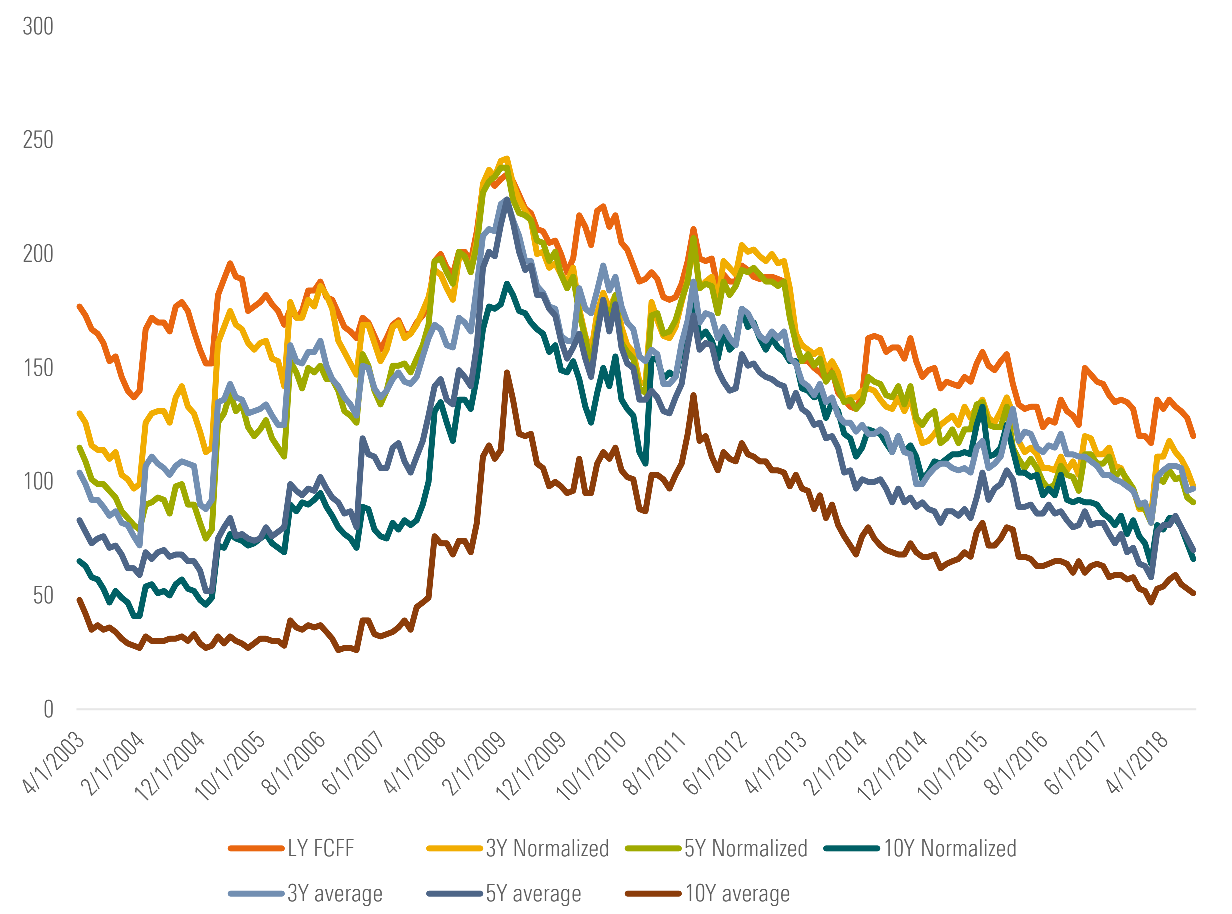
Appendix 5 - WACC Stress Results Across Strategies

	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg.	5Y avg.	10Y avg.	Average
Damodaran (NYU) WACC								
Ann. Excess return	15,81%	15,61%	13,39%	13,81%	16,72%	17,81%	24,31%	16,78%
Ann. volatility	17,26%	17,64%	17,25%	18,65%	18,49%	19,73%	35,83%	20,69%
Sharpe ratio	0,92	0,89	0,78	0,74	0,90	0,90	0,68	0,83
Cumulative return	10,89	10,44	7,51	7,68	12,10	13,84	23,58	12,29
Bloomberg WACC								
	LY FCFF	**3Y Norm**	**5Y Norm**	**10Y Norm**	**3Y avg.**	**5Y avg.**	**10Y avg.**	**Average**
Ann. Excess return	14,58%	14,63%	13,57%	13,21%	15,27%	15,84%	17,36%	14,92%
Ann. volatility	15,16%	15,06%	14,51%	14,52%	15,39%	15,53%	17,70%	15,41%
Sharpe ratio	0,96	0,97	0,94	0,91	0,99	1,02	0,98	0,97
Cumulative return	9,50	9,59	8,26	7,81	10,50	11,41	13,72	10,11
Morningstar sample WACC								
	LY FCFF	**3Y Norm**	**5Y Norm**	**10Y Norm**	**3Y avg.**	**5Y avg.**	**10Y avg.**	**Average**
Ann. Excess return	14,54%	13,97%	12,87%	12,90%	15,50%	15,53%	17,34%	14,66%
Ann. volatility	14,90%	14,71%	14,29%	14,16%	15,11%	15,18%	17,08%	15,06%
Sharpe ratio	0,98	0,95	0,90	0,91	1,03	1,02	1,02	0,97
Cumulative return	9,49	8,73	7,44	7,50	10,95	10,97	13,87	9,85
Equal sector WACC (9%)								
	LY FCFF	**3Y Norm**	**5Y Norm**	**10Y Norm**	**3Y avg.**	**5Y avg.**	**10Y avg.**	**Average**
Ann. Excess return	14,84%	14,35%	13,52%	13,24%	16,14%	16,55%	17,49%	15,16%
Ann. volatility	15,97%	15,93%	15,77%	16,05%	16,57%	17,20%	21,57%	17,01%
Sharpe ratio	0,93	0,90	0,86	0,83	0,97	0,96	0,81	0,89
Cumulative return	9,70	9,00	7,95	7,56	11,66	12,21	12,57	10,09

Performance measures for Gordon's growth strategies with different WACC estimates applied.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples., Bloomberg, Damodaran (NYU), 9%
Source: Morningstar Direct, Kenneth French database, and own estimations.
Market & Period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 6 - Trading Signals for Gordon Growth Strategies



Number of monthly trades for Gordon growth strategies over time.

Source: Own estimation & Morningstar Direct
Market & Period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 7 - Correlations Between Gordon Growth Strategies

	LY FCFF	3Y norm	5Y norm	10Y norm	3Y avg.	5Y avg.	10Y avg.
LY FCFF	1,00	0,99	0,99	0,98	0,99	0,99	0,93
3Y norm		1,00	0,99	0,99	0,99	0,98	0,90
5Y norm			1,00	0,99	0,98	0,98	0,89
10Y norm				1,00	0,98	0,97	0,89
3Y avg.					1,00	0,99	0,94
5Y avg.						1,00	0,95
10Y avg.							1,00

Correlations between Gordon growth strategy returns.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Market & Period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 8 - Decile Performance of the Gordon Growth Models

Panel Last year FCFF	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Ann. excess return	**10,87%**	**10,48%**	**10,86%**	**12,18%**	**10,72%**	**13,02%**	**14,31%**	**13,85%**	**13,97%**	**17,79%**	**6,92%**
t-values	2,70	2,63	2,76	3,30	2,97	3,74	4,00	3,73	3,16	3,51	2,40
Alpha (MKT)	**-0,17%**	**-0,78%**	**-0,22%**	**1,84%**	**0,71%**	**3,19%**	**4,34%**	**3,40%**	**1,78%**	**4,66%**	**4,83%**
t-values	0,11	0,58	0,16	1,37	0,51	2,73	3,25	2,61	1,01	1,80	1,68
Alpha (S&P 500)	**0,32%**	**-0,32%**	**0,19%**	**2,26%**	**1,09%**	**3,54%**	**4,72%**	**3,80%**	**2,22%**	**5,18%**	**4,87%**
t-values	0,18	0,21	0,13	1,56	0,75	2,86	3,33	2,73	1,21	1,94	1,70
Alpha (S&P 500 adj.)	**-1,76%**	**-2,31%**	**-1,75%**	**0,42%**	**-0,80%**	**1,88%**	**2,79%**	**2,02%**	**-0,11%**	**2,20%**	**3,97%**
t-values	1,18	1,81	1,38	0,33	0,67	1,69	2,58	1,61	0,08	1,04	1,40
3-factor alpha (MKT)	**-0,50%**	**-1,15%**	**-0,49%**	**1,53%**	**0,49%**	**3,08%**	**4,42%**	**3,48%**	**2,04%**	**5,22%**	**5,72%**
t-values	0,32	0,92	0,37	1,22	0,36	2,67	3,35	2,69	1,19	2,15	2,17
3-factor alpha (S&P 500 adj.)	**-0,86%**	**-1,41%**	**-0,79%**	**1,30%**	**0,10%**	**2,86%**	**3,98%**	**3,23%**	**1,47%**	**4,27%**	**5,12%**
t-values	0,59	1,16	0,64	1,07	0,08	2,56	3,64	2,60	1,03	2,16	1,96
Beta (MKT)	**1,07**	**1,09**	**1,07**	**1,00**	**0,97**	**0,95**	**0,96**	**1,01**	**1,18**	**1,27**	**0,20**
t-values	31,42	38,59	37,46	35,94	33,77	39,25	34,66	37,26	32,19	23,61	3,38
Beta (S&P 500)	**1,08**	**1,11**	**1,09**	**1,02**	**0,99**	**0,97**	**0,98**	**1,03**	**1,20**	**1,29**	**0,21**
t-values	28,53	34,60	34,82	32,69	31,58	36,74	32,35	34,56	30,52	22,52	3,42
Beta (S&P 500 adj.)	**1,01**	**1,02**	**1,01**	**0,94**	**0,92**	**0,89**	**0,92**	**0,94**	**1,12**	**1,24**	**0,24**
t-values	35,11	41,75	41,41	39,29	40,39	41,67	44,27	39,22	39,37	30,54	4,32
Information ratio (MKT)	**-0,03**	**-0,15**	**-0,04**	**0,36**	**0,13**	**0,71**	**0,85**	**0,68**	**0,26**	**0,47**	**0,44**
Information ratio (S&P 500)	**0,05**	**-0,06**	**0,03**	**0,41**	**0,19**	**0,75**	**0,87**	**0,71**	**0,31**	**0,50**	**0,44**
Information ratio (S&P 500 adj.)	**-0,31**	**-0,48**	**-0,36**	**0,09**	**-0,18**	**0,44**	**0,68**	**0,42**	**-0,02**	**0,27**	**0,37**
Adj. R^2	**0,87**	**0,92**	**0,91**	**0,91**	**0,88**	**0,91**	**0,89**	**0,90**	**0,87**	**0,80**	**0,22**
Sharpe ratio	**0,69**	**0,67**	**0,70**	**0,84**	**0,76**	**0,95**	**1,02**	**0,95**	**0,80**	**0,89**	**0,61**

Panel 3Y Norm FCFF	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Ann. excess return	**10,87%**	**14,25%**	**10,36%**	**10,55%**	**11,81%**	**13,53%**	**12,74%**	**15,65%**	**13,85%**	**16,34%**	**5,48%**
t-values	2,65	3,36	2,75	2,87	3,29	3,85	3,61	3,73	3,28	3,40	2,04
Alpha (MKT)	**-0,17%**	**-0,78%**	**-0,22%**	**1,84%**	**0,71%**	**3,19%**	**4,34%**	**3,40%**	**1,78%**	**4,66%**	**4,83%**
t-values	0,22	1,51	0,23	0,13	1,38	2,83	2,16	2,17	1,31	1,58	1,41
Alpha (S&P 500)	**0,13%**	**3,05%**	**0,13%**	**0,55%**	**2,10%**	**4,12%**	**3,34%**	**5,59%**	**2,74%**	**3,94%**	**3,81%**
t-values	0,07	1,68	0,10	0,42	1,57	2,93	2,32	2,29	1,49	1,73	1,41
Alpha (S&P 500 adj.)	**-2,01%**	**0,88%**	**-1,65%**	**-1,25%**	**0,31%**	**2,37%**	**1,56%**	**3,22%**	**0,59%**	**1,28%**	**3,29%**
t-values	1,31	0,57	1,33	1,10	0,27	1,95	1,27	1,55	0,37	0,70	1,22
3-factor alpha (MKT)	**-0,81%**	**2,14%**	**-0,65%**	**-0,01%**	**1,48%**	**3,62%**	**2,85%**	**5,36%**	**2,55%**	**3,82%**	**4,63%**
t-values	0,51	1,36	0,56	0,01	1,24	2,78	2,07	2,26	1,43	1,85	1,86
3-factor alpha (S&P 500 adj.)	**-1,17%**	**1,82%**	**-0,85%**	**-0,27%**	**1,22%**	**3,34%**	**2,47%**	**4,60%**	**2,02%**	**3,13%**	**4,30%**
t-values	0,79	1,22	0,73	0,24	1,08	2,74	2,04	2,22	1,31	1,80	1,73
Beta (MKT)	**1,09**	**1,13**	**1,03**	**1,01**	**0,98**	**0,95**	**0,94**	**1,01**	**1,11**	**1,25**	**0,16**
t-values	30,96	32,44	39,78	39,56	38,13	34,47	32,86	20,22	29,84	27,67	2,89
Beta (S&P 500)	**1,10**	**1,15**	**1,05**	**1,03**	**1,00**	**0,97**	**0,96**	**1,03**	**1,14**	**1,27**	**0,17**
t-values	28,14	29,49	35,90	36,29	34,87	32,00	31,20	19,69	28,81	26,12	2,96
Beta (S&P 500 adj.)	**1,03**	**1,07**	**0,96**	**0,94**	**0,92**	**0,89**	**0,89**	**0,99**	**1,06**	**1,20**	**0,17**
t-values	34,92	35,88	40,18	43,12	42,10	38,18	37,88	24,91	34,87	34,29	3,37
Information ratio (MKT)	**-0,06**	**0,39**	**-0,06**	**0,03**	**0,36**	**0,74**	**0,56**	**0,57**	**0,34**	**0,41**	**0,37**
Information ratio (S&P 500)	**0,02**	**0,44**	**0,03**	**0,11**	**0,41**	**0,76**	**0,60**	**0,60**	**0,39**	**0,45**	**0,37**
Information ratio (S&P 500 adj.)	**-0,34**	**0,15**	**-0,35**	**-0,29**	**0,07**	**0,51**	**0,33**	**0,41**	**0,10**	**0,18**	**0,32**
Adj. R^2	**0,88**	**0,89**	**0,93**	**0,92**	**0,92**	**0,89**	**0,88**	**0,72**	**0,85**	**0,85**	**0,20**
Sharpe ratio	**0,67**	**0,85**	**0,70**	**0,73**	**0,84**	**0,98**	**0,92**	**0,95**	**0,83**	**0,86**	**0,52**

Panel 5Y Norm FCFF	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Ann. excess return	**11,81%**	**13,18%**	**10,26%**	**11,26%**	**11,74%**	**13,18%**	**12,11%**	**12,93%**	**13,38%**	**15,39%**	**3,58%**
t-values	2,68	3,11	2,70	3,07	3,39	3,88	3,53	3,71	3,36	3,19	1,31
Alpha (MKT)	**-0,37%**	**2,54%**	**-0,29%**	**0,15%**	**1,70%**	**3,74%**	**2,99%**	**5,21%**	**2,35%**	**3,42%**	**3,80%**
t-values	0,23	0,86	0,26	0,68	1,64	3,12	1,98	2,51	1,54	1,12	1,06
Alpha (S&P 500)	**0,11%**	**1,97%**	**0,08%**	**1,17%**	**2,39%**	**3,93%**	**2,92%**	**3,48%**	**2,57%**	**3,07%**	**2,96%**
t-values	0,06	1,08	0,05	0,95	1,83	3,25	2,13	2,69	1,74	1,29	1,06
Alpha (S&P 500 adj.)	**-2,16%**	**-0,18%**	**-1,78%**	**-0,49%**	**0,77%**	**2,29%**	**1,13%**	**1,79%**	**0,55%**	**0,35%**	**2,51%**
t-values	1,41	0,12	1,34	0,41	0,64	2,14	1,02	1,57	0,45	0,19	0,90
3-factor alpha (MKT)	**-0,82%**	**0,92%**	**-0,75%**	**0,48%**	**1,91%**	**3,54%**	**2,50%**	**3,26%**	**2,29%**	**2,99%**	**3,81%**
t-values	0,51	0,62	0,58	0,47	1,55	3,07	1,93	2,59	1,61	1,40	1,49
3-factor alpha (S&P 500 adj.)	**-1,21%**	**0,69%**	**-0,97%**	**0,40%**	**1,71%**	**3,28%**	**2,11%**	**2,93%**	**1,83%**	**2,26%**	**3,47%**
t-values	0,83	0,47	0,77	0,34	1,41	3,06	1,91	2,61	1,55	1,26	1,35
Beta (MKT)	**1,18**	**1,14**	**1,03**	**1,02**	**0,94**	**0,93**	**0,92**	**0,95**	**1,08**	**1,24**	**0,06**
t-values	33,40	33,38	35,64	44,30	36,40	38,64	34,19	36,05	36,67	26,25	1,05
Beta (S&P 500)	**1,20**	**1,15**	**1,04**	**1,03**	**0,96**	**0,95**	**0,94**	**0,97**	**1,11**	**1,26**	**0,06**
t-values	30,56	29,51	32,23	39,37	34,15	36,61	32,08	35,01	35,19	24,80	1,06
Beta (S&P 500 adj.)	**1,11**	**1,07**	**0,96**	**0,94**	**0,88**	**0,87**	**0,88**	**0,89**	**1,02**	**1,20**	**0,09**
t-values	37,93	35,58	37,73	41,09	37,86	42,34	41,33	40,54	43,67	32,86	1,59
Information ratio (MKT)	**-0,06**	**0,23**	**-0,07**	**0,18**	**0,43**	**0,81**	**0,52**	**0,66**	**0,40**	**0,29**	**0,28**
Information ratio (S&P 500)	**0,02**	**0,28**	**0,01**	**0,25**	**0,48**	**0,85**	**0,56**	**0,70**	**0,45**	**0,34**	**0,28**
Information ratio (S&P 500 adj.)	**-0,37**	**-0,03**	**-0,35**	**-0,11**	**0,17**	**0,56**	**0,27**	**0,41**	**0,12**	**0,05**	**0,24**
Adj. R^2	**0,89**	**0,91**	**0,91**	**0,95**	**0,90**	**0,91**	**0,89**	**0,90**	**0,90**	**0,83**	**0,18**
Sharpe ratio	**0,68**	**0,79**	**0,69**	**0,78**	**0,86**	**0,99**	**0,90**	**0,94**	**0,85**	**0,81**	**0,33**

Panel 10Y Norm FCFF	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Ann. excess return	**11,02%**	**10,13%**	**11,89%**	**10,65%**	**12,88%**	**12,31%**	**13,53%**	**12,23%**	**12,79%**	**14,58%**	**3,55%**
t-values	2,54	2,37	3,01	2,94	3,64	3,53	4,12	3,51	3,20	3,14	1,18
Alpha (MKT)	**-0,39%**	**1,42%**	**-0,36%**	**0,75%**	**2,04%**	**3,60%**	**2,57%**	**3,17%**	**2,19%**	**2,55%**	**2,95%**
t-values	0,45	1,08	0,58	0,37	2,43	1,97	3,57	1,96	1,12	1,07	1,08
Alpha (S&P 500)	**-0,29%**	**-1,19%**	**1,34%**	**0,90%**	**3,21%**	**2,94%**	**4,67%**	**2,77%**	**2,19%**	**2,99%**	**3,28%**
t-values	0,15	0,65	0,83	0,64	2,58	2,14	3,72	2,17	1,31	1,23	1,07
Alpha (S&P 500 adj.)	**-2,55%**	**-3,45%**	**-0,70%**	**-0,85%**	**1,65%**	**1,36%**	**3,08%**	**1,24%**	**0,20%**	**0,46%**	**3,00%**
t-values	1,54	2,31	0,53	0,68	1,33	1,03	2,75	0,98	0,14	0,22	0,97
3-factor alpha (MKT)	**-1,30%**	**-2,22%**	**0,54%**	**0,32%**	**2,77%**	**2,31%**	**4,32%**	**2,62%**	**2,23%**	**3,11%**	**4,41%**
t-values	0,76	1,53	0,39	0,27	2,38	1,82	3,50	2,07	1,40	1,43	1,59
3-factor alpha (S&P 500 adj.)	**-1,69%**	**-2,49%**	**0,23%**	**0,15%**	**2,67%**	**2,13%**	**3,99%**	**2,36%**	**1,71%**	**2,42%**	**4,12%**
t-values	1,08	1,77	0,18	0,12	2,15	1,67	3,65	1,97	1,28	1,28	1,48
Beta (MKT)	**1,15**	**1,15**	**1,07**	**0,99**	**0,97**	**0,94**	**0,89**	**0,94**	**1,06**	**1,17**	**0,02**
t-values	30,35	33,93	35,04	37,28	39,94	34,51	34,74	35,76	30,74	23,76	0,32
Beta (S&P 500)	**1,16**	**1,16**	**1,08**	**1,00**	**0,99**	**0,96**	**0,91**	**0,97**	**1,09**	**1,19**	**0,03**
t-values	27,58	29,76	31,35	33,49	37,21	32,59	33,79	35,43	30,37	22,76	0,42
Beta (S&P 500 adj.)	**1,08**	**1,08**	**1,01**	**0,92**	**0,90**	**0,87**	**0,83**	**0,88**	**1,01**	**1,13**	**0,04**
t-values	34,01	37,89	39,28	38,45	37,62	34,59	38,84	36,37	35,88	28,57	0,74
Information ratio (MKT)	**-0,12**	**-0,28**	**0,15**	**0,10**	**0,63**	**0,51**	**0,93**	**0,51**	**0,29**	**0,28**	**0,28**
Information ratio (S&P 500)	**-0,04**	**-0,17**	**0,22**	**0,17**	**0,67**	**0,56**	**0,97**	**0,57**	**0,34**	**0,32**	**0,28**
Information ratio (S&P 500 adj.)	**-0,40**	**-0,61**	**-0,14**	**-0,18**	**0,35**	**0,27**	**0,72**	**0,26**	**0,04**	**0,06**	**0,25**
Adj. R^2	**0,87**	**0,91**	**0,91**	**0,91**	**0,92**	**0,89**	**0,89**	**0,90**	**0,87**	**0,81**	**0,21**
Sharpe ratio	**0,65**	**0,60**	**0,76**	**0,75**	**0,92**	**0,90**	**1,05**	**0,89**	**0,81**	**0,80**	**0,30**

Panel 3Y avg FCFF	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Ann. excess return	**11,91%**	**9,90%**	**9,37%**	**11,13%**	**11,61%**	**13,29%**	**14,19%**	**15,73%**	**14,55%**	**17,13%**	**5,22%**
t-values	2,97	2,53	2,48	3,02	3,16	3,73	3,85	4,30	3,68	3,25	1,74
Alpha (MKT)	**-0,82%**	**-1,76%**	**0,85%**	**0,47%**	**2,84%**	**2,59%**	**4,38%**	**2,49%**	**1,86%**	**2,52%**	**3,34%**
t-values	0,47	0,70	0,88	0,56	0,99	2,60	2,89	3,94	2,37	1,29	0,96
Alpha (S&P 500)	**1,17%**	**-0,53%**	**-0,81%**	**1,06%**	**1,69%**	**3,68%**	**4,22%**	**5,97%**	**3,96%**	**4,06%**	**2,89%**
t-values	0,72	0,33	0,55	0,82	1,21	2,70	3,04	3,99	2,52	1,44	0,98
Alpha (S&P 500 adj.)	**-0,90%**	**-2,32%**	**-2,64%**	**-0,63%**	**-0,12%**	**1,83%**	**2,27%**	**4,10%**	**2,00%**	**0,80%**	**1,71%**
t-values	0,68	1,51	2,02	0,51	0,10	1,67	2,11	3,26	1,46	0,38	0,59
3-factor alpha (MKT)	**0,30%**	**-1,50%**	**-1,57%**	**0,42%**	**1,15%**	**3,07%**	**3,95%**	**5,56%**	**3,83%**	**4,08%**	**3,78%**
t-values	0,22	1,14	1,21	0,37	0,92	2,50	2,98	3,93	2,62	1,57	1,40
3-factor alpha (S&P 500 adj.)	**-0,03%**	**-1,56%**	**-1,82%**	**0,27%**	**0,91%**	**2,73%**	**3,50%**	**5,19%**	**3,44%**	**2,88%**	**2,91%**
t-values	0,02	1,07	1,46	0,22	0,76	2,52	3,24	4,11	2,65	1,45	1,10
Beta (MKT)	**1,09**	**1,06**	**1,03**	**1,01**	**1,00**	**0,97**	**1,00**	**0,98**	**1,06**	**1,32**	**0,23**
t-values	35,09	34,66	35,86	40,91	37,55	36,81	35,99	33,29	34,05	23,04	3,74
Beta (S&P 500)	**1,10**	**1,07**	**1,04**	**1,03**	**1,02**	**0,99**	**1,02**	**1,00**	**1,09**	**1,34**	**0,24**
t-values	31,77	30,92	33,28	37,39	34,05	33,73	34,36	31,25	32,21	22,17	3,77
Beta (S&P 500 adj.)	**1,02**	**0,98**	**0,96**	**0,94**	**0,94**	**0,92**	**0,95**	**0,93**	**1,00**	**1,30**	**0,28**
t-values	39,92	33,14	38,26	39,93	40,40	43,49	46,11	38,47	38,19	31,73	5,04
Information ratio (MKT)	**0,12**	**-0,18**	**-0,23**	**0,15**	**0,26**	**0,68**	**0,75**	**1,03**	**0,62**	**0,34**	**0,25**
Information ratio (S&P 500)	**0,19**	**-0,09**	**-0,14**	**0,21**	**0,32**	**0,70**	**0,79**	**1,04**	**0,66**	**0,38**	**0,25**
Information ratio (S&P 500 adj.)	**-0,18**	**-0,40**	**-0,53**	**-0,13**	**-0,03**	**0,44**	**0,55**	**0,86**	**0,38**	**0,10**	**0,15**
Adj. R^2	**0,91**	**0,91**	**0,91**	**0,93**	**0,91**	**0,91**	**0,90**	**0,88**	**0,89**	**0,79**	**0,24**
Sharpe ratio	**0,75**	**0,64**	**0,63**	**0,77**	**0,80**	**0,95**	**0,98**	**1,09**	**0,93**	**0,83**	**0,44**

Panel 5Y avg FCFF	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Ann. excess return	**10,50%**	**12,73%**	**13,91%**	**10,04%**	**12,08%**	**12,80%**	**13,27%**	**14,22%**	**13,32%**	**17,68%**	**7,18%**
t-values	2,61	3,02	3,57	2,73	3,49	3,61	3,62	3,84	3,35	3,36	2,15
Alpha (MKT)	**0,70%**	**-1,02%**	**-1,21%**	**0,66%**	**1,27%**	**3,28%**	**3,86%**	**5,59%**	**3,56%**	**3,54%**	**2,84%**
t-values	0,37	0,67	2,13	0,28	1,97	2,25	2,19	2,87	1,50	1,51	1,48
Alpha (S&P 500)	**-0,14%**	**1,64%**	**3,41%**	**0,06%**	**2,65%**	**3,22%**	**3,51%**	**4,24%**	**2,59%**	**4,85%**	**4,99%**
t-values	0,08	0,90	2,28	0,04	2,12	2,41	2,33	3,00	1,69	1,65	1,49
Alpha (S&P 500 adj.)	**-2,07%**	**-0,56%**	**1,44%**	**-1,65%**	**0,95%**	**1,59%**	**1,54%**	**2,53%**	**0,66%**	**1,62%**	**3,69%**
t-values	1,35	0,37	1,15	1,31	0,88	1,27	1,30	1,91	0,48	0,70	1,12
3-factor alpha (MKT)	**-1,11%**	**0,56%**	**2,80%**	**-0,48%**	**2,04%**	**2,86%**	**3,12%**	**4,03%**	**2,28%**	**4,87%**	**5,98%**
t-values	0,76	0,38	2,03	0,39	1,85	2,23	2,21	3,02	1,54	1,77	1,96
3-factor alpha (S&P 500 adj.)	**-1,37%**	**0,23%**	**2,46%**	**-0,67%**	**1,82%**	**2,64%**	**2,67%**	**3,79%**	**1,92%**	**3,66%**	**5,03%**
t-values	0,97	0,16	1,96	0,54	1,70	2,10	2,25	2,93	1,42	1,68	1,68
Beta (MKT)	**1,07**	**1,12**	**1,06**	**1,01**	**0,95**	**0,96**	**0,98**	**1,00**	**1,08**	**1,29**	**0,22**
t-values	32,42	32,35	36,12	38,84	39,81	36,00	33,23	35,69	34,85	21,50	3,11
Beta (S&P 500)	**1,09**	**1,14**	**1,08**	**1,02**	**0,97**	**0,98**	**1,00**	**1,02**	**1,10**	**1,32**	**0,22**
t-values	29,95	29,11	33,53	35,53	36,12	34,32	30,97	33,70	33,42	20,81	3,13
Beta (S&P 500 adj.)	**1,00**	**1,06**	**1,00**	**0,93**	**0,89**	**0,89**	**0,94**	**0,93**	**1,01**	**1,28**	**0,28**
t-values	34,07	36,37	41,18	38,67	42,84	37,04	41,33	36,71	38,86	28,95	4,42
Information ratio (MKT)	**-0,10**	**0,17**	**0,56**	**-0,07**	**0,51**	**0,59**	**0,57**	**0,75**	**0,39**	**0,39**	**0,39**
Information ratio (S&P 500)	**-0,02**	**0,23**	**0,59**	**0,01**	**0,55**	**0,63**	**0,61**	**0,78**	**0,44**	**0,43**	**0,39**
Information ratio (S&P 500 adj.)	**-0,35**	**-0,10**	**0,30**	**-0,34**	**0,23**	**0,33**	**0,34**	**0,50**	**0,13**	**0,18**	**0,29**
Adj. R^2	**0,90**	**0,90**	**0,90**	**0,91**	**0,92**	**0,90**	**0,88**	**0,90**	**0,89**	**0,76**	**0,23**
Sharpe ratio	**0,66**	**0,77**	**0,91**	**0,69**	**0,89**	**0,92**	**0,92**	**0,98**	**0,85**	**0,85**	**0,55**

Panel 10Y avg FCFF	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Ann. excess return	**10,18%**	**12,07%**	**12,34%**	**10,39%**	**12,50%**	**11,80%**	**13,20%**	**14,55%**	**13,40%**	**16,92%**	**6,75%**
t-values	2,56	2,90	3,30	2,72	3,56	3,17	3,64	3,90	3,46	3,16	1,92
Alpha (MKT)	**-0,59%**	**1,11%**	**3,00%**	**-0,34%**	**2,26%**	**2,88%**	**3,12%**	**3,87%**	**2,22%**	**4,35%**	**4,94%**
t-values	0,10	0,12	0,12	0,10	0,13	0,11	0,13	0,15	0,13	0,17	0,08
Alpha (S&P 500)	**9,45%**	**11,53%**	**12,27%**	**10,00%**	**12,56%**	**11,28%**	**12,55%**	**14,78%**	**13,15%**	**17,15%**	**7,71%**
t-values	0,31	0,61	1,57	0,05	2,24	1,24	2,40	3,17	1,95	1,29	1,24
Alpha (S&P 500 adj.)	**-2,23%**	**-1,06%**	**0,51%**	**-1,73%**	**1,42%**	**-0,02%**	**1,55%**	**2,60%**	**1,14%**	**0,60%**	**2,84%**
t-values	1,46	0,69	0,38	1,32	1,11	0,01	1,37	2,18	0,83	0,25	0,83
3-factor alpha (MKT)	**-1,40%**	**0,23%**	**1,61%**	**-0,38%**	**2,54%**	**1,38%**	**3,11%**	**4,15%**	**2,97%**	**3,82%**	**5,22%**
t-values	1,05	0,14	1,21	0,29	2,02	1,04	2,33	3,08	1,97	1,39	1,63
3-factor alpha (S&P 500 adj.)	**-1,50%**	**-0,14%**	**1,36%**	**-0,59%**	**2,38%**	**1,12%**	**2,70%**	**3,77%**	**2,52%**	**2,69%**	**4,19%**
t-values	1,05	0,10	1,05	0,45	1,86	0,88	2,37	3,19	1,94	1,21	1,33
Beta (MKT)	**1,09**	**1,06**	**1,03**	**1,01**	**1,00**	**0,97**	**1,00**	**0,98**	**1,06**	**1,32**	**0,23**
t-values	0,01	0,08	0,10	0,04	0,05	0,04	0,07	0,11	0,08	0,15	0,15
Beta (S&P 500)	**1,09**	**1,12**	**1,03**	**1,06**	**0,97**	**1,03**	**0,99**	**1,03**	**1,06**	**1,34**	**0,25**
t-values	32,50	28,42	33,30	34,57	33,49	33,21	31,70	34,25	32,02	20,96	3,32
Beta (S&P 500 adj.)	**0,99**	**1,05**	**0,94**	**0,97**	**0,88**	**0,94**	**0,93**	**0,95**	**0,98**	**1,30**	**0,31**
t-values	33,62	35,67	36,89	38,46	36,02	38,62	42,86	41,72	37,03	28,63	4,76
Information ratio (MKT)	**-0,17**	**0,09**	**0,36**	**-0,07**	**0,54**	**0,27**	**0,59**	**0,79**	**0,46**	**0,30**	**0,32**
Information ratio (S&P 500)	**1,57**	**1,63**	**2,21**	**1,82**	**2,42**	**2,04**	**2,23**	**2,73**	**2,21**	**1,50**	**0,58**
Information ratio (S&P 500 adj.)	**-0,38**	**-0,18**	**0,10**	**-0,35**	**0,29**	**0,00**	**0,36**	**0,57**	**0,22**	**0,07**	**0,22**
Adj. R^2	**0,91**	**0,88**	**0,90**	**0,91**	**0,90**	**0,90**	**0,89**	**0,90**	**0,88**	**0,77**	**0,22**
Sharpe ratio	**0,65**	**0,74**	**0,84**	**0,69**	**0,90**	**0,81**	**0,92**	**0,99**	**0,88**	**0,80**	**0,49**

Gordon's growth strategy performance measures divided into declies.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 9 - Fundamentals for Gordon Growth Strategies

Panel A: Fundamentals LY FCFF	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Book/Market	0.32	0.31	0.30	0.29	0.30	0.31	0.33	0.37	0.44	0.61	0.28
Sales/Market	0.69	0.64	0.70	0.70	0.75	0.77	0.85	1.03	1.30	1.94	1.25
FCFF/EV	0.9%	1.9%	2.8%	3.6%	4.3%	5.1%	5.8%	7.2%	9.6%	17.4%	16.5%
EBITDA/EV	8.0%	8.5%	8.9%	9.2%	9.5%	10.3%	10.7%	11.0%	12.1%	13.1%	5.0%
ROIC	18.1%	16.2%	19.7%	16.3%	20.0%	17.9%	20.9%	19.9%	17.8%	14.9%	-3.1%
EBITDA margin	24.1%	23.8%	21.7%	21.9%	21.4%	21.7%	21.1%	20.5%	20.1%	13.9%	-10.2%
EBIT margin	16.4%	17.1%	15.8%	15.9%	16.0%	16.2%	15.2%	14.5%	13.4%	5.5%	-10.9%
NIBD/Equity	0.69	0.38	-0.19	-0.25	0.63	0.66	0.63	0.73	0.78	0.50	-0.20
Earnings/Price	3.4%	4.1%	3.8%	4.3%	4.3%	4.9%	5.0%	4.9%	4.8%	0.8%	-2.7%
1Y Revenue growth	11.4%	10.9%	7.1%	7.5%	7.7%	6.6%	6.1%	4.1%	4.5%	-0.4%	-11.8%
Panel A: Fundamentals 3Y Normalized FCFF	**P1 (Low)**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10 (High)**	**H-L**
Book/Market	0.34	0.32	0.32	0.30	0.30	0.30	0.31	0.34	0.40	0.55	0.21
Sales/Market	0.71	0.71	0.67	0.69	0.76	0.76	0.86	0.97	1.15	1.89	1.18
FCFF/EV	1.1%	1.7%	1.8%	2.8%	3.6%	4.2%	4.7%	6.1%	7.4%	13.1%	12.0%
EBITDA/EV	7.6%	7.9%	8.2%	9.5%	10.4%	10.0%	10.6%	11.4%	12.6%	14.6%	7.0%
ROIC	15.0%	12.7%	20.8%	19.8%	21.8%	13.8%	21.4%	22.7%	20.5%	15.7%	0.7%
EBITDA margin	22.2%	21.3%	20.5%	22.4%	21.3%	21.8%	21.0%	21.7%	21.0%	18.3%	-3.8%
EBIT margin	13.9%	15.3%	14.6%	16.5%	15.8%	16.2%	15.5%	15.7%	14.6%	11.5%	-2.4%
NIBD/Equity	0.44	0.40	0.16	-0.31	-0.02	0.64	0.71	0.69	0.68	0.62	0.18
Earnings/Price	2.7%	3.1%	3.2%	4.4%	4.6%	5.1%	5.0%	5.1%	5.5%	2.9%	0.2%
1Y Revenue growth	11.9%	9.4%	8.3%	6.9%	7.3%	7.2%	6.7%	6.2%	4.3%	1.5%	-10.4%
Panel A: Fundamentals 5Y Normalized FCFF	**P1 (Low)**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10 (High)**	**H-L**
Book/Market	0.35	0.32	0.33	0.31	0.30	0.30	0.31	0.33	0.38	0.54	0.20
Sales/Market	0.01	0.02	0.02	0.04	0.03	0.04	0.05	0.05	0.07	0.11	0.10
FCFF/EV	0.8%	1.9%	2.3%	3.5%	3.4%	3.8%	4.5%	5.3%	7.2%	11.0%	10.2%
EBITDA/EV	7.3%	7.6%	8.1%	9.3%	9.6%	10.3%	10.5%	11.4%	13.3%	15.6%	8.2%
ROIC	13.6%	13.5%	16.6%	16.8%	20.4%	14.2%	26.9%	24.2%	21.2%	18.5%	4.9%
EBITDA margin	21.1%	21.5%	20.4%	20.6%	21.1%	22.0%	21.2%	21.5%	22.0%	19.0%	-2.1%
EBIT margin	13.7%	14.6%	14.1%	15.7%	15.7%	16.6%	16.0%	16.2%	15.9%	11.8%	-1.9%
NIBD/Equity	0.33	0.46	0.25	0.80	0.43	0.44	0.74	0.66	0.40	0.73	0.40
Earnings/Price	2.3%	3.4%	3.5%	4.4%	4.8%	5.3%	5.3%	5.5%	6.1%	4.7%	2.4%
1Y Revenue growth	9.9%	9.7%	8.9%	6.7%	7.1%	7.0%	7.0%	7.2%	4.9%	1.5%	-8.4%
Panel A: Fundamentals 10Y Normalized FCFF	**P1 (Low)**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10 (High)**	**H-L**
Book/Market	0.35	0.35	0.34	0.31	0.30	0.32	0.31	0.32	0.37	0.48	0.13
Sales/Market	0.73	0.77	0.74	0.72	0.75	0.80	0.88	0.94	1.03	1.62	0.89
FCFF/EV	1.1%	2.2%	3.1%	3.4%	3.1%	4.0%	5.3%	5.2%	8.2%	9.0%	7.9%
EBITDA/EV	7.3%	8.0%	8.6%	8.8%	9.4%	10.2%	10.5%	11.6%	13.7%	16.6%	9.3%
ROIC	12.3%	16.7%	19.4%	18.1%	24.1%	25.1%	23.8%	29.4%	23.3%	21.9%	9.6%
EBITDA margin	20.0%	21.1%	20.7%	20.8%	21.4%	21.2%	20.9%	21.3%	21.5%	19.8%	-0.2%
EBIT margin	13.1%	14.3%	15.2%	15.8%	16.2%	16.0%	15.7%	16.1%	16.2%	13.5%	0.5%
NIBD/Equity	0.39	0.41	0.59	0.62	0.30	0.34	0.64	0.74	0.26	0.82	0.42
Earnings/Price	2.5%	3.5%	3.9%	4.1%	4.8%	5.0%	5.5%	5.8%	6.4%	6.2%	3.8%
1Y Revenue growth	11.0%	8.4%	6.8%	7.1%	7.3%	6.3%	6.0%	5.7%	5.8%	4.0%	-7.0%

Panel A: Fundamentals 3Y average FCFF	P1 (Low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (High)	H-L
Book/Market	0.31	0.31	0.32	0.30	0.28	0.30	0.33	0.37	0.42	0.60	0.29
Sales/Market	0.65	0.65	0.70	0.73	0.78	0.85	0.89	1.02	1.20	1.99	1.34
FCFF/EV	1.2%	1.4%	2.3%	3.2%	3.9%	4.5%	5.4%	6.1%	8.1%	14.0%	12.8%
EBITDA/EV	7.6%	7.8%	8.6%	9.3%	9.8%	10.1%	10.5%	11.6%	12.7%	13.5%	5.9%
ROIC	14.7%	20.7%	19.5%	15.3%	19.3%	19.7%	24.5%	20.2%	19.3%	12.9%	-1.8%
EBITDA margin	22.7%	21.9%	21.6%	21.7%	21.0%	20.7%	21.0%	21.4%	20.4%	17.2%	-5.5%
EBIT margin	15.7%	15.8%	15.6%	16.1%	15.8%	15.7%	15.4%	15.2%	13.2%	11.1%	-4.6%
NIBD/Equity	0.37	0.18	0.45	0.28	0.20	0.16	0.36	0.54	0.68	0.42	0.05
Earnings/Price	3.5%	3.6%	4.2%	4.3%	4.7%	4.7%	4.6%	4.4%	5.0%	1.5%	-2.0%
1Y Revenue growth	14.3%	10.9%	9.0%	7.2%	6.4%	5.9%	5.0%	3.2%	0.8%	-4.3%	-18.6%
Panel A: Fundamentals 5Y average FCFF	**P1 (Low)**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10 (High)**	**H-L**
Book/Market	0.33	0.32	0.33	0.32	0.28	0.30	0.33	0.35	0.38	0.57	0.24
Sales/Market	0.63	0.60	0.67	0.76	0.78	0.86	0.90	0.97	1.14	1.92	1.29
FCFF/EV	0.6%	2.1%	2.8%	3.5%	3.9%	4.4%	5.6%	6.0%	7.0%	11.8%	11.2%
EBITDA/EV	7.9%	7.9%	8.8%	9.3%	9.2%	10.0%	10.6%	11.5%	12.5%	13.3%	5.4%
ROIC	16.0%	15.7%	20.5%	16.0%	19.1%	17.9%	27.0%	25.1%	20.0%	12.3%	-3.6%
EBITDA margin	22.4%	22.9%	22.3%	21.2%	21.0%	21.1%	21.2%	21.2%	20.7%	16.6%	-5.9%
EBIT margin	15.5%	15.1%	16.3%	15.5%	15.7%	15.9%	15.9%	15.9%	15.0%	10.9%	-4.6%
NIBD/Equity	0.40	0.32	0.36	0.30	0.12	0.37	0.96	0.55	0.18	0.47	0.07
Earnings/Price	3.6%	3.5%	3.8%	4.4%	4.4%	4.7%	5.0%	5.4%	5.6%	2.7%	-0.9%
1Y Revenue growth	14.1%	10.5%	9.0%	7.1%	7.0%	5.8%	4.2%	3.5%	1.7%	-3.0%	-17.2%
Panel A: Fundamentals 10Y average FCFF	**P1 (Low)**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10 (High)**	**H-L**
Book/Market	0.32	0.32	0.33	0.32	0.31	0.32	0.31	0.33	0.38	0.49	0.17
Sales/Market	0.63	0.68	0.69	0.77	0.80	0.88	0.92	0.93	1.22	1.75	1.11
FCFF/EV	1.9%	2.1%	2.7%	3.0%	4.0%	4.5%	5.0%	5.2%	7.3%	12.5%	10.6%
EBITDA/EV	8.5%	8.3%	9.1%	9.4%	9.4%	9.7%	10.3%	10.3%	12.4%	13.7%	5.3%
ROIC	18.9%	15.4%	16.8%	22.9%	27.0%	27.9%	28.1%	26.3%	21.8%	15.9%	-3.0%
EBITDA margin	22.8%	20.9%	22.7%	21.6%	20.8%	20.3%	19.5%	20.4%	19.9%	17.2%	-5.6%
EBIT margin	16.4%	15.1%	16.7%	16.1%	15.7%	14.9%	14.6%	15.6%	14.4%	12.5%	-3.9%
NIBD/Equity	-0.26	-0.26	0.32	0.36	0.39	0.41	0.48	0.47	0.69	0.56	0.81
Earnings/Price	3.8%	4.2%	4.3%	4.5%	4.5%	4.5%	4.5%	4.9%	5.7%	3.0%	-0.7%
1Y Revenue growth	13.2%	10.6%	9.1%	7.2%	6.0%	4.1%	4.3%	3.2%	2.3%	-2.5%	-15.7%

The tables above illustrate different fundamentals for the decile portfolios for Gordon’s growth trading strategies.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 10 - Gordon Growth Quartile Portfolios

Panel Last year FCFF	Q1 (Low)	Q2	Q3	Q4 (High)	H-L
Excess annualized return	**10,93%**	**11,12%**	**13,75%**	**17,14%**	**6,21%**
t-values	2,81	3,11	3,99	3,79	2,94
Alpha (MKT)	**-0,29%**	**0,86%**	**3,83%**	**4,89%**	**5,18%**
t-values	-0,26	0,82	4,01	2,48	2,42
Alpha (S&P 500)	**0,18%**	**1,26%**	**4,20%**	**5,36%**	**5,18%**
t-values	0,05	0,35	1,22	1,19	2,41
Alpha (S&P 500 adj.)	**-1,85%**	**-0,60%**	**2,40%**	**2,66%**	**4,51%**
t-values	2,01	0,70	3,25	1,82	2,13
3-factor alpha (MKT)	**-0,62%**	**0,59%**	**3,83%**	**5,27%**	**5,89%**
t-values	-0,63	0,61	4,07	2,82	3,03
3-factor alpha (S&P 500 adj.)	**8,67%**	**9,39%**	**11,99%**	**14,60%**	**5,93%**
t-values	1,08	0,34	4,64	3,25	2,78
Beta (MKT)	**1,09**	**0,99**	**0,96**	**1,19**	**0,10**
t-values	47,83	45,47	48,22	28,89	2,25
Beta (S&P 500)	**1,10**	**1,01**	**0,98**	**1,21**	**0,11**
t-values	40,92	40,29	43,28	27,36	2,30
Beta (S&P 500 adj.)	**1,02**	**0,94**	**0,91**	**1,16**	**0,14**
t-values	57,82	56,31	63,81	41,31	3,33
Information ratio (MKT)	**-0,07**	**0,21**	**1,04**	**0,65**	**0,63**
Information ratio (S&P 500)	**0,04**	**0,28**	**1,04**	**0,68**	**0,63**
Information ratio (S&P 500 adj.)	**-0,53**	**-0,18**	**0,85**	**0,48**	**0,56**
Adj. R^2	**0,96**	**0,95**	**0,95**	**0,86**	**0,21**
Sharpe ratio	**0,71**	**0,79**	**1,01**	**0,96**	**0,75**

Panel 3Y Norm FCFF	Q1 (Low)	Q2	Q3	Q4 (High)	H-L
Excess annualized return	**12,11%**	**11,04%**	**14,13%**	**14,63%**	**2,51%**
t-values	0,27	0,65	3,24	2,05	1,57
Alpha (MKT)	**0,73%**	**0,78%**	**4,22%**	**2,75%**	**2,02%**
t-values	0,57	0,85	3,25	1,78	1,05
Alpha (S&P 500)	**1,22%**	**1,17%**	**4,59%**	**3,19%**	**1,97%**
t-values	0,30	0,33	1,28	0,75	1,02
Alpha (S&P 500 adj.)	**-0,90%**	**-0,58%**	**2,64%**	**0,84%**	**1,74%**
t-values	0,82	0,68	2,62	0,72	0,90
3-factor alpha (MKT)	**0,31%**	**0,56%**	**4,14%**	**3,03%**	**2,72%**
t-values	0,27	0,65	3,24	2,05	1,57
3-factor alpha (S&P 500 adj.)	**10,08%**	**9,31%**	**12,60%**	**11,93%**	**1,86%**
t-values	0,02	0,41	3,61	2,23	1,41
Beta (MKT)	**1,10**	**0,99**	**0,96**	**1,15**	**0,05**
t-values	41,46	51,97	35,55	35,82	1,18
Beta (S&P 500)	**1,12**	**1,01**	**0,98**	**1,17**	**0,06**
t-values	36,00	45,20	33,10	33,56	1,36
Beta (S&P 500 adj.)	**1,04**	**0,93**	**0,92**	**1,10**	**0,06**
t-values	49,58	57,07	47,33	49,42	1,67
Information ratio (MKT)	**0,15**	**0,22**	**0,85**	**0,47**	**0,27**
Information ratio (S&P 500)	**0,22**	**0,29**	**0,87**	**0,51**	**0,27**
Information ratio (S&P 500 adj.)	**-0,22**	**-0,18**	**0,69**	**0,19**	**0,24**
Adj. R^2	**0,94**	**0,97**	**0,90**	**0,91**	**0,22**
Sharpe ratio	**0,77**	**0,79**	**1,01**	**0,88**	**0,34**

Panel 5Y Norm FCFF	Q1 (Low)	Q2	Q3	Q4 (High)	H-L
Excess annualized return	**12,44%**	**10,85%**	**13,10%**	**13,58%**	**1,14%**
t-values	3,03	3,08	3,93	3,28	0,62
Alpha (MKT)	**0,75%**	**0,62%**	**3,55%**	**1,88%**	**1,13%**
t-values	0,58	0,70	3,57	1,34	0,60
Alpha (S&P 500)	**1,26%**	**1,02%**	**3,89%**	**2,30%**	**1,04%**
t-values	0,30	0,29	1,15	0,55	0,56
Alpha (S&P 500 adj.)	**-0,88%**	**-0,66%**	**2,19%**	**0,03%**	**0,92%**
t-values	0,78	0,74	2,66	0,03	0,48
3-factor alpha (MKT)	**0,26%**	**0,43%**	**3,52%**	**2,12%**	**1,86%**
t-values	0,23	0,51	3,56	1,56	1,12
3-factor alpha (S&P 500 adj.)	**10,45%**	**8,95%**	**11,62%**	**11,04%**	**0,59%**
t-values	0,04	0,31	3,91	1,60	0,96
Beta (MKT)	**1,13**	**0,99**	**0,93**	**1,13**	**0,00**
t-values	42,10	53,31	44,70	38,78	0,02
Beta (S&P 500)	**1,15**	**1,01**	**0,95**	**1,16**	**0,01**
t-values	36,35	45,72	41,32	36,26	0,25
Beta (S&P 500 adj.)	**1,06**	**0,92**	**0,87**	**1,08**	**0,02**
t-values	1,06	0,92	0,87	1,08	0,02
Information ratio (MKT)	**0,15**	**0,18**	**0,93**	**0,35**	**0,16**
Information ratio (S&P 500)	**0,22**	**0,26**	**0,95**	**0,40**	**0,14**
Information ratio (S&P 500 adj.)	**-0,20**	**-0,19**	**0,70**	**0,01**	**0,13**
Adj. R^2	**0,95**	**0,97**	**0,94**	**0,92**	**0,25**
Sharpe ratio	**0,77**	**0,78**	**1,00**	**0,83**	**0,16**

Panel 10Y Norm FCFF	Q1 (Low)	Q2	Q3	Q4 (High)	H-L
Excess annualized return	**10,84%**	**11,76%**	**13,02%**	**13,29%**	**2,45%**
t-values	2,62	3,33	3,98	3,27	1,15
Alpha (MKT)	**-0,89%**	**1,50%**	**3,60%**	**2,00%**	**2,89%**
t-values	-0,64	1,70	3,95	1,29	1,33
Alpha (S&P 500)	**-0,34%**	**1,90%**	**3,92%**	**2,38%**	**2,72%**
t-values	-0,08	0,53	1,19	0,58	1,26
Alpha (S&P 500 adj.)	**-2,59%**	**0,20%**	**2,35%**	**0,22%**	**2,81%**
t-values	2,21	0,23	2,76	0,17	1,28
3-factor alpha (MKT)	**-1,36%**	**1,38%**	**3,49%**	**2,42%**	**3,78%**
t-values	-1,14	1,63	3,84	1,69	2,03
3-factor alpha (S&P 500 adj.)	**8,83%**	**10,34%**	**11,50%**	**10,83%**	**2,00%**
t-values	1,61	1,38	3,94	1,72	1,90
Beta (MKT)	**1,14**	**0,99**	**0,91**	**1,09**	**-0,04**
t-values	39,52	54,16	48,10	34,07	-0,94
Beta (S&P 500)	**1,15**	**1,01**	**0,93**	**1,12**	**-0,03**
t-values	33,86	46,02	44,84	32,75	-0,61
Beta (S&P 500 adj.)	**1,07**	**0,92**	**0,85**	**1,04**	**-0,03**
t-values	47,65	54,13	52,07	43,74	-0,69
Information ratio (MKT)	**-0,17**	**0,44**	**1,03**	**0,34**	**0,35**
Information ratio (S&P 500)	**-0,06**	**0,48**	**1,05**	**0,39**	**0,33**
Information ratio (S&P 500 adj.)	**-0,58**	**0,06**	**0,72**	**0,05**	**0,34**
Adj. R^2	**0,94**	**0,97**	**0,95**	**0,90**	**0,29**
Sharpe ratio	**0,66**	**0,84**	**1,01**	**0,83**	**0,29**

Panel 3Y avg FCFF	Q1 (Low)	Q2	Q3	Q4 (High)	H-L
Excess annualized return	**10,50%**	**11,07%**	**14,06%**	**17,59%**	**7,09%**
t-values	2,71	3,12	3,92	4,00	3,24
Alpha (MKT)	**-0,63%**	**0,80%**	**3,82%**	**5,81%**	**6,45%**
t-values	-0,57	0,87	3,51	2,87	2,88
Alpha (S&P 500)	**-0,17%**	**1,21%**	**4,19%**	**6,27%**	**6,44%**
t-values	-0,04	0,34	1,17	1,42	2,90
Alpha (S&P 500 adj.)	**-2,12%**	**-0,51%**	**2,29%**	**3,59%**	**5,72%**
t-values	2,06	0,57	2,79	2,39	2,57
3-factor alpha (MKT)	**-1,05%**	**0,58%**	**3,77%**	**6,17%**	**7,22%**
t-values	-1,08	0,68	3,49	3,20	3,60
3-factor alpha (S&P 500 adj.)	**8,57%**	**9,29%**	**12,10%**	**15,16%**	**6,58%**
t-values	1,36	0,46	4,05	3,74	3,28
Beta (MKT)	**1,08**	**0,99**	**0,99**	**1,14**	**0,06**
t-values	46,40	51,94	43,77	27,09	1,33
Beta (S&P 500)	**1,09**	**1,01**	**1,01**	**1,16**	**0,07**
t-values	39,92	44,45	40,06	25,77	1,39
Beta (S&P 500 adj.)	**1,01**	**0,92**	**0,94**	**1,12**	**0,11**
t-values	50,92	53,70	59,72	38,74	2,57
Information ratio (MKT)	**-0,15**	**0,23**	**0,91**	**0,75**	**0,75**
Information ratio (S&P 500)	**-0,03**	**0,30**	**0,93**	**0,78**	**0,75**
Information ratio (S&P 500 adj.)	**-0,54**	**-0,15**	**0,73**	**0,63**	**0,68**
Adj. R^2	**0,96**	**0,97**	**0,94**	**0,84**	**0,22**
Sharpe ratio	**0,69**	**0,79**	**1,00**	**1,02**	**0,82**

Panel 5Y avg FCFF	Q1 (Low)	Q2	Q3	Q4 (High)	H-L
Excess annualized return	**11,90%**	**11,80%**	**12,81%**	**17,78%**	**5,88%**
t-values	3,01	3,35	3,71	4,01	2,71
Alpha (MKT)	**0,60%**	**1,58%**	**2,88%**	**5,81%**	**5,21%**
t-values	0,50	1,77	2,96	2,96	2,35
Alpha (S&P 500)	**1,08%**	**1,97%**	**3,24%**	**6,25%**	**5,18%**
t-values	0,27	0,56	0,93	1,41	2,35
Alpha (S&P 500 adj.)	**-0,96%**	**0,21%**	**1,51%**	**3,56%**	**4,52%**
t-values	0,91	0,27	1,80	2,54	2,05
3-factor alpha (MKT)	**0,12%**	**1,42%**	**2,92%**	**6,10%**	**5,98%**
t-values	0,11	1,65	3,04	3,23	3,01
3-factor alpha (S&P 500 adj.)	**9,84%**	**10,01%**	**11,39%**	**15,06%**	**5,22%**
t-values	0,19	1,48	3,16	3,87	2,71
Beta (MKT)	**1,09**	**0,99**	**0,96**	**1,16**	**0,07**
t-values	43,62	53,43	47,55	28,41	1,42
Beta (S&P 500)	**1,11**	**1,01**	**0,98**	**1,18**	**0,07**
t-values	37,95	45,94	43,20	27,09	1,52
Beta (S&P 500 adj.)	**1,03**	**0,93**	**0,90**	**1,14**	**0,11**
t-values	50,36	60,44	55,99	42,14	2,56
Information ratio (MKT)	**0,13**	**0,46**	**0,77**	**0,77**	**0,61**
Information ratio (S&P 500)	**0,21**	**0,50**	**0,80**	**0,80**	**0,61**
Information ratio (S&P 500 adj.)	**-0,24**	**0,07**	**0,47**	**0,67**	**0,54**
Adj. R^2	**0,96**	**0,97**	**0,95**	**0,85**	**0,22**
Sharpe ratio	**0,76**	**0,85**	**0,94**	**1,02**	**0,69**

Panel 10Y avg FCFF	Q1 (Low)	Q2	Q3	Q4 (High)	H-L
Excess annualized return	**11,22%**	**11,75%**	**12,70%**	**17,38%**	**6,16%**
t-values	2,91	3,28	3,52	3,91	2,60
Alpha (MKT)	**0,14%**	**1,39%**	**2,35%**	**5,67%**	**5,53%**
t-values	0,11	0,12	0,13	0,18	0,07
Alpha (S&P 500)	**10,80%**	**11,50%**	**12,48%**	**17,64%**	**6,84%**
t-values	0,16	0,49	0,76	1,37	2,28
Alpha (S&P 500 adj.)	**-1,30%**	**0,04%**	**0,83%**	**3,45%**	**4,75%**
t-values	1,19	0,04	1,05	2,05	1,97
3-factor alpha (MKT)	**-0,28%**	**1,28%**	**2,36%**	**6,06%**	**6,33%**
t-values	-0,28	1,38	2,34	2,91	2,88
3-factor alpha (S&P 500 adj.)	**9,37%**	**9,96%**	**10,93%**	**14,79%**	**5,42%**
t-values	0,50	1,18	2,51	3,23	2,56
Beta (MKT)	**1,07**	**1,00**	**1,00**	**1,13**	**0,06**
t-values	45,72	50,60	45,99	25,23	1,21
Beta (S&P 500)	**1,09**	**1,02**	**1,02**	**1,16**	**0,07**
t-values	39,36	44,68	40,59	24,43	1,34
Beta (S&P 500 adj.)	**1,00**	**0,94**	**0,95**	**1,11**	**0,11**
t-values	47,82	54,08	62,66	34,50	2,44
Information ratio (MKT)	**0,03**	**0,38**	**0,59**	**0,68**	**0,60**
Information ratio (S&P 500)	**2,18**	**2,80**	**2,77**	**2,08**	**0,74**
Information ratio (S&P 500 adj.)	**-0,31**	**0,01**	**0,28**	**0,54**	**0,52**
Adj. R^2	**0,96**	**0,96**	**0,95**	**0,81**	**0,20**
Sharpe ratio	**0,74**	**0,83**	**0,89**	**0,99**	**0,66**

Performance measures for Gordon growth strategy divided into quartile portfolios.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 11 - Growth Stress in the Gordon Growth Portfolios

Growth: 3.84%							
Simple investment strategy	**LY FCFF**	**3Y Norm**	**5Y Norm**	**10Y Norm**	**3Y avg.**	**5Y avg.**	**10Y avg.**
Excess return	14.49%	13.89%	12.83%	12.93%	15.53%	15.68%	17.42%
CAPM alpha	4.86%	4.41%	3.54%	3.89%	5.88%	6.02%	7.61%
t-stat	4.17	3.82	3.47	3.34	4.41	4.15	3.06
3-factor alpha	4.99%	4.48%	3.63%	4.13%	6.02%	6.18%	7.90%
t-stat	4.46	3.97	3.63	3.69	4.67	4.40	3.23
MKT beta	1.00	1.00	0.98	0.96	1.00	1.00	1.00
t-stat	39.23	38.66	42.96	37.41	33.95	31.12	17.83
SMB beta	0.13	0.12	0.08	0.04	0.13	0.14	0.16
t-stat	3.15	2.74	2.24	0.87	2.77	2.70	1.77
HML beta	0.11	0.07	0.07	0.16	0.12	0.13	0.21
t-stat	2.84	1.71	2.11	4.09	2.66	2.69	2.50
Sharpe ratio	0.97	0.94	0.90	0.91	1.02	1.02	1.01
Information ratio (3-factor)	1.12	1.01	0.93	0.93	1.18	1.11	0.83
Adjusted R^2 (3-factor)	93.89%	93.48%	94.94%	92.97%	91.44%	89.73%	72.71%
Growth: 2.83%							
Simple investment strategy	**LY FCFF**	**3Y Norm**	**5Y Norm**	**10Y Norm**	**3Y avg.**	**5Y avg.**	**10Y avg.**
Excess return	15.15%	13.75%	13.43%	13.95%	16.35%	17.22%	20.05%
CAPM alpha	5.30%	3.88%	3.63%	4.33%	6.33%	7.12%	9.73%
t-stat	3.88	2.97	3.04	2.88	3.85	3.73	2.13
3-factor alpha	5.48%	3.99%	3.74%	4.61%	6.57%	7.33%	10.04%
t-stat	4.20	3.15	3.21	3.23	4.18	4.02	2.22
MKT beta	1.01	1.03	1.02	0.99	1.02	1.01	1.00
t-stat	34.00	35.43	38.47	30.28	28.36	24.33	9.71
SMB beta	0.15	0.13	0.11	0.12	0.17	0.24	0.32
t-stat	3.15	2.63	2.53	2.28	2.83	3.47	1.89
HML beta	0.14	0.10	0.09	0.20	0.18	0.18	0.26
t-stat	3.16	2.31	2.23	4.06	3.37	2.88	1.68
Sharpe ratio	0.98	0.89	0.89	0.91	1.02	1.04	0.87
Information ratio (3-factor)	1.05	0.80	0.82	0.80	1.04	1.00	0.57
Adjusted R^2 (3-factor)	91.63%	92.11%	93.43%	89.36%	87.93%	84.24%	45.69%

Performance measures and sector loadings for Gordon growth strategies for different growth rates.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.84% & 2.83%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Growth: 6%							
	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg	5Y avg.	10Y avg.
Technology	-3%	-4%	-4%	-4%	-3%	-3%	-3%
Consumer Cyclical	1%	0%	0%	-1%	1%	0%	-1%
Healthcare	1%	2%	2%	3%	1%	2%	3%
Energy	-3%	-3%	-3%	-4%	-3%	-3%	-3%
Communication Services	-1%	-1%	-1%	-1%	-1%	-1%	-1%
Consumer Defensive	5%	6%	6%	6%	5%	6%	7%
Industrials	2%	2%	2%	2%	2%	1%	1%
Basic Materials	0%	0%	0%	1%	0%	0%	0%
Utilities	0%	-1%	0%	0%	0%	0%	1%
Real Estate	-2%	-2%	-2%	-3%	-2%	-2%	-3%

Growth: 0%							
	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y avg	5Y avg.	10Y avg.
Technology	5%	9%	10%	11%	8%	9%	12%
Consumer Cyclical	3%	5%	7%	9%	8%	9%	13%
Healthcare	-1%	-2%	-3%	-2%	-2%	-2%	-2%
Energy	-1%	-2%	-4%	-2%	-3%	-4%	-5%
Communication Services	-1%	-1%	-1%	-2%	-2%	-2%	-3%
Consumer Defensive	0%	0%	-1%	0%	-1%	-1%	-1%
Industrials	-2%	-2%	-2%	-2%	-1%	-2%	-5%
Basic Materials	0%	0%	0%	-2%	0%	0%	1%
Utilities	-2%	-4%	-3%	-5%	-4%	-5%	-6%
Real Estate	-3%	-4%	-4%	-4%	-4%	-3%	-4%

Sector exposure of the long-only Gordon Growth portfolios with different growth rates.

Weighting: Equal weighted and monthly rebalancing
Growth: 0% & 6%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09..

Growth: 0%							
Simple investment strategy	**LY FCFF**	**3Y Norm**	**5Y Norm**	**10Y Norm**	**3Y avg.**	**5Y avg.**	**10Y avg.**
Excess return	17,38%	15,68%	16,30%	14,07%	18,15%	21,41%	35,96%
CAPM alpha	6,38%	4,21%	4,94%	2,59%	6,71%	10,45%	25,54%
t-stat	2,64	1,96	2,29	0,87	2,13	2,35	2,08
3-factor alpha	6,70%	4,41%	5,10%	2,99%	7,04%	10,80%	26,15%
t-stat	2,90	2,16	2,50	1,07	2,31	2,46	2,14
MKT beta	1,09	1,14	1,12	1,08	1,11	1,06	0,93
t-stat	20,56	24,32	24,06	16,97	15,92	10,58	3,32
SMB beta	0,26	0,27	0,32	0,42	0,32	0,33	0,55
t-stat	2,94	3,56	4,19	4,04	2,81	2,01	1,19
HML beta	0,25	0,19	0,17	0,34	0,27	0,29	0,49
t-stat	3,17	2,66	2,42	3,53	2,60	1,90	1,17
Sharpe ratio	0,94	0,84	0,88	0,69	0,88	0,92	0,73
Information ratio (3-factor)	0,72	0,54	0,62	0,26	0,58	0,63	0,56
Adjusted R^2 (3-factor)	79,12%	84,19%	84,14%	73,99%	69,49%	50,04%	11,18%
Growth: 6%							
S&P 500: 2003-2018 Simple investment strategy	**LY FCFF**	**3Y Norm**	**5Y Norm**	**10Y Norm**	**3Y avg.**	**5Y avg.**	**10Y avg.**
Excess return	13,76%	13,41%	13,11%	13,05%	14,07%	14,33%	14,32%
CAPM alpha	4,27%	4,06%	3,95%	4,06%	4,72%	5,06%	5,15%
t-stat	4,44	4,56	4,55	4,44	4,79	4,96	4,33
3-factor alpha	4,31%	4,04%	3,96%	4,15%	4,76%	5,13%	5,33%
t-stat	4,65	4,64	4,63	4,63	4,97	5,11	4,62
MKT beta	1,00	0,99	0,98	0,96	0,99	0,98	0,96
t-stat	47,05	50,03	50,11	46,81	45,04	42,88	36,63
SMB beta	0,13	0,11	0,09	0,08	0,12	0,09	0,08
t-stat	3,66	3,38	2,94	2,23	3,30	2,38	1,89
HML beta	0,05	0,01	0,02	0,07	0,05	0,06	0,13
t-stat	1,67	0,38	0,74	2,33	1,57	1,82	3,20
Sharpe ratio	0,95	0,94	0,93	0,94	0,98	1,00	1,00
Information ratio (3-factor)	1,17	1,18	1,19	1,18	1,26	1,31	1,17
Adjusted R^2 (3-factor)	96,15%	96,70%	96,70%	96,00%	95,60%	94,91%	92,66%

Performance measures and sector loadings for Gordon’s growth strategies for different growth rates.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.84% & 2,83%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 12 - Long/Short Lagged Returns Gordon Growth Strategies

Gordon growth lagged returns Long-Short	LY FCFF	3Y Norm	5Y Norm	10Y Norm	3Y Average	5Y Average	10Y Average
Excess return	3,24%	2,26%	0,96%	1,01%	4,23%	1,53%	2,28%
CAPM alpha	2,80%	2,28%	0,74%	0,89%	3,89%	1,25%	2,01%
t-stat	1,71	1,18	0,44	0,47	2,13	0,72	1,11
3-factor alpha	3,04%	2,47%	1,85%	2,45%	4,21%	1,79%	2,33%
t-stat	2,12	1,40	1,23	1,50	2,60	1,16	1,44
MKT beta	0,03	-0,01	-0,06	-0,09	0,01	-0,01	0,00
t-stat	0,80	-0,28	-1,67	-2,49	0,32	-0,25	-0,02
SMB beta	-0,04	-0,05	-0,13	-0,21	-0,05	-0,08	-0,03
t-stat	-0,70	-0,69	-2,26	-3,34	-0,87	-1,36	-0,49
HML beta	0,37	0,39	0,36	0,43	0,40	0,39	0,39
t-stat	7,50	6,36	7,00	7,66	7,18	7,42	7,05
Sharpe ratio	0,51	0,30	0,15	0,14	0,60	0,23	0,33
Information ratio (3-factor)	0,48	0,33	0,28	0,33	0,60	0,27	0,33
Adjusted R^2 (3-factor)	26,46%	19,16%	23,29%	28,89%	24,00%	24,62%	22,94%

Long short Gordon growth strategies with 1 month lagged returns.

Weighting: Value weighted and monthly rebalancing
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 13 - Long/Short Value Driver Performance

Value driver portfolios 30/30 long/short	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	**4.02%**	**3.01%**	**2.40%**	**2.32%**	**2.31%**	**4.22%**	**4.61%**	**5.25%**
t-values	2.12	1.38	1.21	1.17	1.22	1.90	2.08	2.39
Alpha (MKT)	**3.74%**	**1.56%**	**1.75%**	**2.02%**	**2.35%**	**3.38%**	**3.72%**	**4.80%**
t-values	1.92	0.71	0.86	0.99	1.21	1.50	1.65	2.13
Alpha (S&P 500)	**3.71%**	**1.59%**	**1.74%**	**1.99%**	**2.29%**	**3.35%**	**3.68%**	**4.76%**
t-values	1.91	0.73	0.86	0.98	1.18	1.49	1.64	2.12
Alpha (S&P 500 adj.)	**3.37%**	**1.00%**	**1.37%**	**1.73%**	**2.14%**	**2.81%**	**3.17%**	**4.22%**
t-values	1.72	0.46	0.67	0.85	1.10	1.25	1.41	1.88
3-factor alpha (MKT)	**4.28%**	**2.31%**	**2.30%**	**2.63%**	**2.95%**	**4.10%**	**4.49%**	**5.56%**
t-values	2.34	1.17	1.20	1.39	1.64	1.97	2.20	2.73
3-factor alpha (S&P 500 adj.)	**3.86%**	**1.75%**	**1.89%**	**2.29%**	**2.67%**	**3.48%**	**3.92%**	**4.97%**
t-values	2.10	0.90	0.98	1.20	1.47	1.68	1.92	2.42
Beta (MKT)	**0.03**	**0.14**	**0.06**	**0.03**	**0.00**	**0.08**	**0.09**	**0.04**
t-values	0.67	3.10	1.49	0.67	-0.09	1.71	1.82	0.92
Beta (S&P 500)	**0.03**	**0.15**	**0.07**	**0.03**	**0.00**	**0.09**	**0.10**	**0.05**
t-values	0.78	3.11	1.55	0.77	0.06	1.84	1.98	1.04
Beta (S&P 500 adj.)	**0.05**	**0.16**	**0.08**	**0.05**	**0.01**	**0.11**	**0.11**	**0.08**
t-values	1.39	3.86	2.12	1.19	0.36	2.59	2.66	1.91
Information ratio (MKT)	**0.50**	**0.19**	**0.23**	**0.26**	**0.32**	**0.40**	**0.43**	**0.56**
Information ratio (SP500)	**0.50**	**0.19**	**0.23**	**0.26**	**0.31**	**0.39**	**0.43**	**0.55**
Information ratio (S&P 500 adj.)	**0.45**	**0.12**	**0.18**	**0.22**	**0.29**	**0.33**	**0.37**	**0.49**
Adjusted R^2 (3-factor)	**0.13**	**0.24**	**0.13**	**0.15**	**0.16**	**0.18**	**0.21**	**0.20**
Sharpe ratio	**0.54**	**0.35**	**0.31**	**0.30**	**0.31**	**0.48**	**0.53**	**0.61**

Illustrates the annualized performance of the long/short value driver portfolios. The portfolios buy the 30% most undervalued stocks and short sell the 30% most overvalued stocks according to their respective valuation model. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

Appendix 14 - Stressing Growth in the Value Driver Models

Value driver portfolios 30/30 long/short	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	**3.60%**	**3.12%**	**2.61%**	**2.31%**	**2.07%**	**4.48%**	**5.49%**	**5.28%**
Alpha (MKT)	**2.73%**	**1.64%**	**1.57%**	**1.29%**	**1.40%**	**3.06%**	**4.10%**	**4.15%**
t-stat	1.35	0.75	0.77	0.64	0.70	1.31	1.82	1.79
3-factor alpha	**3.34%**	**2.40%**	**2.15%**	**1.92%**	**2.02%**	**3.86%**	**4.83%**	**4.98%**
t-stat	1.79	1.22	1.12	1.02	1.09	1.81	2.35	2.42
MKT beta	**0.04**	**0.08**	**0.06**	**0.06**	**0.03**	**0.08**	**0.07**	**0.02**
t-stat	0.92	1.76	1.30	1.35	0.67	1.63	1.52	0.49
SMB beta	**-0.07**	**-0.05**	**-0.06**	**-0.09**	**-0.11**	**-0.09**	**-0.04**	**0.01**
t-stat	-0.95	-0.72	-0.86	-1.31	-1.54	-1.18	-0.57	0.12
HML beta	**0.36**	**0.45**	**0.34**	**0.37**	**0.36**	**0.47**	**0.44**	**0.51**
t-stat	5.61	6.68	5.19	5.66	5.61	6.41	6.18	7.22
Sharpe ratio	**0.46**	**0.36**	**0.33**	**0.29**	**0.27**	**0.49**	**0.62**	**0.59**
Information ratio (3-factor)	**0.43**	**0.29**	**0.27**	**0.25**	**0.26**	**0.43**	**0.56**	**0.56**
Adjusted R^2 (3-factor)	**0.17**	**0.24**	**0.16**	**0.18**	**0.17**	**0.23**	**0.21**	**0.25**

Illustrates the annualized performance of the long/short value driver portfolios and their beta loadings on MKT, SMB, and HML. The portfolios buy the 30% most undervalued stocks and short sell the 30% most overvalued stocks according to their respective valuation model. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 2.83%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

Value driver portfolios Long-only	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	12.56%	14.32%	12.46%	12.34%	12.18%	13.08%	13.32%	13.51%
Alpha (MKT)	3.47%	3.69%	3.36%	3.33%	3.31%	3.91%	4.10%	4.69%
t-stat	3.88	1.73	3.78	3.82	3.73	4.05	3.82	4.02
3-factor alpha	3.41%	4.06%	3.33%	3.32%	3.32%	3.92%	4.18%	4.86%
t-stat	3.85	1.97	3.76	3.84	3.78	4.09	3.94	4.27
MKT beta	0.98	1.07	0.98	0.97	0.95	0.98	0.98	0.93
t-stat	48.45	22.87	48.51	49.08	47.48	44.79	40.45	35.89
SMB beta	0.08	0.13	0.07	0.08	0.07	0.07	0.09	0.08
t-stat	2.39	1.65	2.22	2.60	2.26	1.97	2.18	1.78
HML beta	-0.02	0.26	-0.01	0.01	0.03	0.02	0.06	0.12
t-stat	-0.56	3.61	-0.23	0.26	0.91	0.71	1.74	3.02
Sharpe ratio	0.90	0.82	0.89	0.89	0.89	0.93	0.93	0.97
Information ratio (3-factor)	0.99	0.50	0.97	0.99	0.98	1.06	1.01	1.08
Adjusted R^2 (3-factor)	0.96	0.82	0.96	0.96	0.96	0.95	0.94	0.92

Factor loadings and performance measures for the long-only portfolios of stocks trading at a price/fair value below 1 based on the estimates of the value driver models. T-values below 1.96 are insignificant at a 95% confidence level and marked in red

Weighting: Equal weighted and monthly rebalancing.
Growth: 6%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

Value driver portfolios 30/30 long/short	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	**3.22%**	**3.20%**	**0.41%**	**1.37%**	**1.27%**	**2.60%**	**4.12%**	**3.93%**
Alpha (MKT)	**5.07%**	**1.79%**	**1.86%**	**3.13%**	**3.90%**	**3.91%**	**5.51%**	**5.88%**
t-stat	2.78	0.80	0.97	1.63	2.03	1.93	2.47	2.66
3-factor alpha	**5.45%**	**2.57%**	**2.31%**	**3.59%**	**4.33%**	**4.46%**	**6.18%**	**6.52%**
t-stat	3.15	1.28	1.27	1.97	2.38	2.35	2.99	3.15
MKT beta	**-0.16**	**0.07**	**-0.13**	**-0.16**	**-0.23**	**-0.13**	**-0.15**	**-0.20**
t-stat	-4.03	1.57	-3.07	-3.91	-5.63	-2.91	-3.26	-4.24
SMB beta	**-0.24**	**-0.06**	**-0.24**	**-0.22**	**-0.26**	**-0.23**	**-0.20**	**-0.22**
t-stat	-3.70	-0.77	-3.49	-3.28	-3.80	-3.22	-2.58	-2.79
HML beta	**0.18**	**0.46**	**0.22**	**0.23**	**0.20**	**0.29**	**0.37**	**0.34**
t-stat	3.06	6.70	3.58	3.72	3.25	4.39	5.19	4.82
Sharpe ratio	**0.44**	**0.37**	**0.05**	**0.18**	**0.16**	**0.33**	**0.47**	**0.44**
Information ratio (3-factor)	**0.78**	**0.30**	**0.31**	**0.49**	**0.59**	**0.57**	**0.72**	**0.77**
Adjusted R^2 (3-factor)	**0.21**	**0.24**	**0.18**	**0.20**	**0.28**	**0.18**	**0.19**	**0.22**

Illustrates the annualized performance of the long/short value driver portfolios and their beta loadings on MKT, SMB, and HML. The portfolios buy the 30% most undervalued stocks and short sell the 30% most overvalued stocks according to their respective valuation model. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 6%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

Value driver portfolios Long-only	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	14.74%	14.85%	14.67%	13.85%	13.09%	19.53%	21.79%	26.67%
Alpha (MKT)	3.85%	3.90%	3.87%	3.18%	2.44%	8.60%	10.66%	15.57%
t-stat	1.64	1.65	1.65	1.34	1.02	2.43	2.16	1.76
3-factor alpha	4.24%	4.28%	4.28%	3.57%	2.85%	9.21%	11.30%	16.28%
t-stat	1.87	1.88	1.89	1.56	1.24	2.69	2.33	1.87
MKT beta	1.09	1.10	1.08	1.07	1.07	1.07	1.06	0.98
t-stat	21.05	21.05	20.88	20.53	20.34	13.61	9.61	4.90
SMB beta	0.16	0.16	0.15	0.14	0.14	0.19	0.26	0.57
t-stat	1.89	1.87	1.74	1.66	1.65	1.45	1.42	1.74
HML beta	0.27	0.27	0.28	0.27	0.29	0.41	0.45	0.56
t-stat	3.52	3.45	3.61	3.47	3.62	3.49	2.69	1.87
Sharpe ratio	0.81	0.81	0.81	0.77	0.72	0.93	0.88	0.71
Information ratio (3-factor)	0.47	0.47	0.47	0.39	0.31	0.68	0.60	0.48
Adjusted R^2 (3-factor)	0.79	0.79	0.79	0.78	0.78	0.62	0.46	0.22

Factor loadings and performance measures for the long-only portfolios of stocks trading at a price/fair value below 1 based on the estimates of the value driver models. T-values below 1.96 are insignificant at a 95% confidence level and marked in red

Weighting: Equal weighted and monthly rebalancing.
Growth: 0%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

Value driver portfolios 30/30 long/short	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	**2.93%**	**2.93%**	**2.87%**	**2.69%**	**2.63%**	**6.34%**	**5.47%**	**6.18%**
Alpha (MKT)	**1.51%**	**1.38%**	**1.23%**	**1.02%**	**0.69%**	**4.53%**	**3.49%**	**4.10%**
t-stat	0.70	0.64	0.57	0.47	0.33	1.78	1.51	1.73
3-factor alpha	**2.24%**	**2.11%**	**1.96%**	**1.74%**	**1.36%**	**5.45%**	**4.33%**	**4.94%**
t-stat	1.15	1.08	1.00	0.89	0.71	2.41	2.12	2.36
MKT beta	**0.08**	**0.09**	**0.10**	**0.10**	**0.13**	**0.09**	**0.10**	**0.10**
t-stat	1.76	2.01	2.23	2.31	2.97	1.80	2.24	2.17
SMB beta	**-0.06**	**-0.05**	**-0.06**	**-0.06**	**-0.04**	**-0.04**	**0.01**	**0.06**
t-stat	-0.81	-0.74	-0.81	-0.83	-0.59	-0.52	0.15	0.71
HML beta	**0.43**	**0.44**	**0.44**	**0.43**	**0.40**	**0.56**	**0.52**	**0.53**
t-stat	6.44	6.50	6.45	6.37	6.03	7.17	7.37	7.36
Sharpe ratio	**0.35**	**0.34**	**0.34**	**0.31**	**0.31**	**0.63**	**0.59**	**0.65**
Information ratio (3-factor)	**0.27**	**0.25**	**0.24**	**0.21**	**0.17**	**0.56**	**0.49**	**0.54**
Adjusted R^2 (3-factor)	**0.23**	**0.24**	**0.24**	**0.24**	**0.25**	**0.27**	**0.30**	**0.30**

Illustrates the annualized performance of the long/short value driver portfolios and their beta loadings on MKT, SMB, and HML. The portfolios buy the 30% most undervalued stocks and short sell the 30% most overvalued stocks according to their respective valuation model. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 0%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09

Appendix 15 - Stressing WACC in the Value Driver Models

WACC = 7% for all stocks:

Value driver portfolios Long-only	**LY ROIC**	**RONIC = WACC**	**3Y Median ROIC**	**5Y Median ROIC**	**10Y Median ROIC**	**3Y Average NOPAT**	**5Y Average NOPAT**	**10Y Average NOPAT**
Annualized excess return	12.73%	14.42%	13.17%	13.04%	12.79%	13.68%	13.96%	14.59%
Alpha (MKT)	3.16%	3.66%	3.60%	3.55%	3.37%	3.87%	3.99%	4.73%
t-stat	3.21	1.92	3.41	3.39	3.25	3.42	3.13	2.92
3-factor alpha	3.19%	3.97%	3.65%	3.60%	3.44%	3.99%	4.16%	5.03%
t-stat	3.31	2.17	3.55	3.52	3.43	3.62	3.40	3.31
MKT beta	1.01	1.09	1.01	1.00	0.99	1.02	1.03	1.00
t-stat	46.01	25.99	42.83	42.87	43.17	40.76	36.81	28.70
SMB beta	0.11	0.15	0.12	0.12	0.11	0.11	0.14	0.18
t-stat	3.04	2.24	2.98	3.00	3.01	2.74	3.01	3.08
HML beta	0.04	0.23	0.06	0.06	0.07	0.09	0.13	0.22
t-stat	1.20	3.60	1.63	1.63	2.09	2.49	3.10	4.27
Sharpe ratio	0.87	0.83	0.89	0.89	0.88	0.91	0.90	0.92
Information ratio (3-factor)	0.85	0.54	0.90	0.90	0.87	0.92	0.85	0.81
Adjusted R^2 (3-factor)	0.96	0.86	0.95	0.95	0.95	0.94	0.93	0.89

Factor loadings and performance measures for the long-only portfolios of stocks trading at a price/fair value below 1 based on the estimates of the value driver models. T-values below 1.96 are insignificant at a 95% confidence level and marked in red

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: 7% for all stocks.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Value driver portfolios 30/30 long/short	**LY ROIC**	**RONIC = WACC**	**3Y Median ROIC**	**5Y Median ROIC**	**10Y Median ROIC**	**3Y Average NOPAT**	**5Y Average NOPAT**	**10Y Average NOPAT**
Annualized excess return	**3.64%**	**3.06%**	**3.60%**	**3.81%**	**3.30%**	**4.59%**	**5.36%**	**4.74%**
Alpha (MKT)	**1.51%**	**0.37%**	**1.32%**	**1.60%**	**1.07%**	**1.98%**	**2.57%**	**2.49%**
t-stat	0.72	0.16	0.58	0.71	0.47	0.84	1.06	0.98
3-factor alpha	**2.15%**	**1.17%**	**2.04%**	**2.31%**	**1.81%**	**2.81%**	**3.41%**	**3.39%**
t-stat	1.12	0.55	0.98	1.13	0.87	1.33	1.58	1.52
MKT beta	**0.14**	**0.17**	**0.14**	**0.14**	**0.14**	**0.17**	**0.18**	**0.10**
t-stat	3.12	3.56	2.92	2.90	2.89	3.52	3.64	2.06
SMB beta	**0.01**	**0.03**	**0.04**	**0.03**	**0.02**	**-0.01**	**0.02**	**0.09**
t-stat	0.19	0.33	0.46	0.37	0.23	-0.07	0.28	1.04
HML beta	**0.40**	**0.50**	**0.45**	**0.45**	**0.46**	**0.51**	**0.52**	**0.57**
t-stat	6.00	6.83	6.22	6.35	6.41	7.02	7.02	7.47
Sharpe ratio	**0.43**	**0.31**	**0.39**	**0.42**	**0.36**	**0.47**	**0.54**	**0.47**
Information ratio (3-factor)	**0.27**	**0.13**	**0.23**	**0.27**	**0.21**	**0.31**	**0.37**	**0.35**
Adjusted R^2 (3-factor)	**0.26**	**0.32**	**0.27**	**0.27**	**0.27**	**0.32**	**0.33**	**0.31**

Illustrates the annualized performance of the long/short value driver portfolios and their beta loadings on MKT, SMB, and HML. The portfolios buy the 30% most undervalued stocks and short sell the 30% most overvalued stocks according to their respective valuation model. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: 7% for all stocks.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Value driver portfolios Sector exposure	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT	S&P 500 adj.
Technology	16%	17%	16%	16%	16%	16%	16%	16%	16%
Consumer Cyclical	21%	23%	21%	21%	20%	21%	21%	22%	18%
Healthcare	13%	10%	13%	13%	13%	12%	12%	12%	13%
Energy	8%	14%	9%	9%	9%	9%	10%	10%	8%
Communication Services	2%	2%	2%	1%	1%	2%	2%	1%	3%
Consumer Defensive	13%	7%	13%	13%	13%	13%	13%	13%	10%
Industrials	19%	16%	19%	19%	20%	18%	19%	18%	15%
Basic Materials	6%	7%	6%	6%	5%	6%	6%	6%	6%
Utilities	3%	4%	3%	3%	2%	3%	3%	2%	7%
Real Estate	0%	0%	0%	0%	0%	0%	0%	0%	4%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Sector exposure of the long-only value driver models. The highest sector exposures are marked in green.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: 7% for all stocks.
Source: Morningstar Direct and own estimations
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09

WACC = 9% for all stocks:

Value driver portfolios Long-only	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	14.25%	14.70%	13.79%	13.55%	13.48%	15.56%	17.82%	19.69%
Alpha (MKT)	3.99%	2.86%	3.30%	3.16%	3.37%	4.88%	6.85%	8.75%
t-stat	2.56	1.05	2.04	1.98	1.95	2.29	2.39	2.03
3-factor alpha	4.13%	3.26%	3.47%	3.32%	3.62%	5.17%	7.22%	9.20%
t-stat	2.72	1.24	2.22	2.14	2.18	2.50	2.59	2.18
MKT beta	1.06	1.16	1.07	1.06	1.03	1.08	1.09	1.05
t-stat	30.45	19.44	29.92	30.12	27.22	22.84	17.07	10.86
SMB beta	0.15	0.23	0.18	0.17	0.14	0.16	0.22	0.33
t-stat	2.64	2.38	2.99	2.89	2.30	2.05	2.07	2.08
HML beta	0.12	0.30	0.14	0.13	0.19	0.21	0.27	0.35
t-stat	2.21	3.29	2.65	2.46	3.29	2.95	2.84	2.41
Sharpe ratio	0.88	0.73	0.83	0.83	0.83	0.88	0.92	0.86
Information ratio (3-factor)	0.69	0.31	0.56	0.54	0.55	0.63	0.66	0.56
Adjusted R^2 (3-factor)	0.89	0.77	0.89	0.89	0.87	0.82	0.72	0.52

Factor loadings and performance measures for the long-only portfolios of stocks trading at a price/fair value below 1 based on the estimates of the value driver models. T-values below 1.96 are insignificant at a 95% confidence level and marked in red

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: 9% for all stocks.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Value driver portfolios 30/30 long/short	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	**3.94%**	**2.68%**	**2.05%**	**2.71%**	**3.07%**	**4.79%**	**5.48%**	**5.50%**
Alpha (MKT)	**2.25%**	**-0.37%**	**-0.09%**	**0.77%**	**1.29%**	**2.39%**	**3.07%**	**3.45%**
t-stat	**3.94%**	**2.68%**	**2.05%**	**2.71%**	**3.07%**	**4.79%**	**5.48%**	**5.50%**
3-factor alpha	**2.25%**	**-0.37%**	**-0.09%**	**0.77%**	**1.29%**	**2.39%**	**3.07%**	**3.45%**
t-stat	1.14	-0.17	-0.04	0.41	0.64	1.06	1.30	1.44
MKT beta	**2.85%**	**0.33%**	**0.52%**	**1.37%**	**1.94%**	**3.17%**	**3.86%**	**4.29%**
t-stat	1.56	0.16	0.29	0.79	1.05	1.55	1.82	2.02
SMB beta	**0.11**	**0.21**	**0.15**	**0.13**	**0.11**	**0.16**	**0.15**	**0.10**
t-stat	2.56	4.57	3.68	3.27	2.63	3.40	3.00	2.14
HML beta	**-0.01**	**0.05**	**-0.02**	**-0.01**	**-0.02**	**-0.02**	**0.04**	**0.04**
t-stat	-0.21	0.70	-0.23	-0.09	-0.26	-0.26	0.45	0.50
Sharpe ratio	**0.37**	**0.45**	**0.37**	**0.37**	**0.40**	**0.47**	**0.49**	**0.52**
Information ratio (3-factor)	5.81	6.39	6.07	6.20	6.24	6.73	6.78	7.18
Adjusted R^2 (3-factor)	**0.50**	**0.28**	**0.26**	**0.35**	**0.38**	**0.52**	**0.57**	**0.58**

Illustrates the annualized performance of the long/short value driver portfolios and their beta loadings on MKT, SMB, and HML. The portfolios buy the 30% most undervalued stocks and short sell the 30% most overvalued stocks according to their respective valuation model. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: 9% for all stocks.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Value driver portfolios Sector exposure	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT	S&P 500 adj.
Technology	20%	19%	20%	21%	21%	20%	20%	21%	16%
Consumer Cyclical	22%	22%	22%	22%	21%	23%	24%	25%	18%
Healthcare	12%	9%	12%	12%	13%	11%	11%	11%	13%
Energy	12%	18%	12%	13%	13%	14%	14%	17%	8%
Communication Services	1%	2%	1%	1%	1%	1%	1%	1%	3%
Consumer Defensive	8%	4%	8%	8%	8%	7%	7%	6%	10%
Industrials	17%	15%	17%	17%	18%	16%	16%	11%	15%
Basic Materials	6%	8%	6%	5%	5%	6%	6%	6%	6%
Utilities	2%	3%	2%	1%	1%	2%	1%	1%	7%
Real Estate	0%	0%	0%	0%	0%	0%	0%	0%	4%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Sector exposure of the long-only value driver models. The highest sector exposures are marked in green.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: 9% for all stocks.
Source: Morningstar Direct and own estimations
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09

WACC = Damodaran (NYU) industry WACC aggregated on the 10 Morningstar sectors

Value driver portfolios Long-only	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	14.21%	15.45%	14.21%	14.20%	12.62%	17.14%	22.14%	31.73%
Alpha (MKT)	3.30%	3.16%	2.92%	3.02%	1.72%	6.03%	11.03%	20.85%
t-stat	1.46	0.96	1.26	1.31	0.68	1.74	2.14	1.71
3-factor alpha	3.55%	3.52%	3.18%	3.31%	2.08%	6.48%	11.59%	21.36%
t-stat	1.61	1.10	1.42	1.48	0.86	1.92	2.28	1.76
MKT beta	1.10	1.20	1.12	1.12	1.08	1.09	1.06	0.95
t-stat	21.84	16.35	21.91	21.95	19.44	14.05	9.15	3.42
SMB beta	0.18	0.27	0.25	0.19	0.23	0.24	0.28	0.69
t-stat	2.23	2.24	2.99	2.31	2.51	1.89	1.48	1.51
HML beta	0.20	0.28	0.22	0.22	0.27	0.33	0.41	0.46
t-stat	2.57	2.56	2.80	2.87	3.24	2.83	2.32	1.11
Sharpe ratio	0.78	0.71	0.76	0.77	0.68	0.82	0.87	0.64
Information ratio (3-factor)	0.41	0.28	0.36	0.37	0.21	0.49	0.59	0.46
Adjusted R^2 (3-factor)	0.80	0.70	0.81	0.81	0.77	0.64	0.43	0.12

Factor loadings and performance measures for the long-only portfolios of stocks trading at a price/fair value below 1 based on the estimates of the value driver models. T-values below 1.96 are insignificant at a 95% confidence level and marked in red

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Damodaran (NYU).
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Value driver portfolios 30/30 long/short	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	**3.71%**	**3.95%**	**2.66%**	**3.23%**	**1.92%**	**3.61%**	**4.84%**	**5.55%**
Alpha (MKT)	**2.12%**	**1.41%**	**0.64%**	**1.33%**	**0.15%**	**1.41%**	**2.78%**	**3.74%**
t-stat	1.09	0.66	0.34	0.73	0.08	0.66	1.25	1.66
3-factor alpha	**2.63%**	**2.09%**	**1.15%**	**1.83%**	**0.63%**	**2.07%**	**3.47%**	**4.46%**
t-stat	1.43	1.06	0.67	1.07	0.36	1.04	1.70	2.19
MKT beta	**0.10**	**0.17**	**0.14**	**0.13**	**0.12**	**0.15**	**0.12**	**0.09**
t-stat	2.43	3.76	3.46	3.24	2.91	3.23	2.64	1.83
SMB beta	**0.00**	**0.04**	**0.03**	**0.03**	**0.02**	**0.00**	**0.03**	**0.07**
t-stat	0.00	0.50	0.48	0.41	0.36	0.04	0.37	0.93
HML beta	**0.32**	**0.42**	**0.32**	**0.31**	**0.30**	**0.40**	**0.43**	**0.46**
t-stat	4.98	6.23	5.43	5.34	5.03	5.93	6.07	6.54
Sharpe ratio	**0.48**	**0.44**	**0.35**	**0.43**	**0.26**	**0.41**	**0.54**	**0.62**
Information ratio (3-factor)	**0.35**	**0.25**	**0.16**	**0.26**	**0.09**	**0.25**	**0.41**	**0.52**
Adjusted R^2 (3-factor)	**0.19**	**0.30**	**0.25**	**0.24**	**0.21**	**0.26**	**0.25**	**0.26**

Illustrates the annualized performance of the long/short value driver portfolios and their beta loadings on MKT, SMB, and HML. The portfolios buy the 30% most undervalued stocks and short sell the 30% most overvalued stocks according to their respective valuation model. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Damodaran (NYU).
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Value driver portfolios Sector exposure	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT	S&P 500 adj.
Technology	20%	18%	22%	22%	22%	20%	20%	22%	16%
Consumer Cyclical	25%	24%	25%	25%	26%	27%	29%	33%	18%
Healthcare	8%	9%	8%	8%	9%	8%	8%	8%	13%
Energy	13%	18%	13%	14%	14%	15%	14%	16%	8%
Communication Services	1%	2%	2%	1%	1%	1%	2%	2%	3%
Consumer Defensive	5%	4%	5%	5%	5%	4%	5%	6%	10%
Industrials	15%	13%	15%	14%	15%	13%	10%	7%	15%
Basic Materials	6%	7%	6%	5%	3%	6%	6%	3%	6%
Utilities	5%	6%	5%	5%	5%	6%	5%	4%	7%
Real Estate	0%	1%	0%	0%	0%	0%	0%	0%	4%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Sector exposure of the long-only value driver models. The highest sector exposures are marked in green.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Damodaran (NYU).
Source: Morningstar Direct and own estimations
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09

WACC = Bloomberg sector consensus

Value driver portfolios Long-only	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	**13.40%**	**13.84%**	**13.29%**	**13.21%**	**12.36%**	**14.51%**	**15.34%**	**16.52%**
Alpha (MKT)	**4.66%**	**3.78%**	**4.44%**	**4.62%**	**4.00%**	**5.52%**	**6.54%**	**8.22%**
t-stat	3.28	1.71	3.13	3.20	2.72	3.36	3.40	3.53
3-factor alpha	**4.84%**	**4.11%**	**4.62%**	**4.84%**	**4.27%**	**5.79%**	**6.88%**	**8.62%**
t-stat	3.43	1.90	3.30	3.40	2.96	3.60	3.67	3.81
MKT beta	**0.93**	**1.03**	**0.94**	**0.92**	**0.90**	**0.94**	**0.92**	**0.85**
t-stat	28.99	20.79	29.47	28.24	27.22	25.73	21.56	16.52
SMB beta	**0.04**	**0.10**	**0.04**	**0.02**	**0.00**	**0.05**	**0.03**	**0.09**
t-stat	0.67	1.29	0.84	0.44	-0.03	0.82	0.46	1.09
HML beta	**0.11**	**0.23**	**0.12**	**0.14**	**0.16**	**0.18**	**0.22**	**0.27**
t-stat	2.33	3.06	2.58	2.85	3.25	3.19	3.42	3.41
Sharpe ratio	**0.95**	**0.81**	**0.93**	**0.94**	**0.90**	**0.98**	**1.02**	**1.08**
Information ratio (3-factor)	**0.89**	**0.48**	**0.85**	**0.87**	**0.76**	**0.92**	**0.93**	**0.97**
Adjusted R^2 (3-factor)	**0.87**	**0.78**	**0.88**	**0.87**	**0.86**	**0.85**	**0.79**	**0.70**

Factor loadings and performance measures for the long-only portfolios of stocks trading at a price/fair value below 1 based on the estimates of the value driver models. T-values below 1.96 are insignificant at a 95% confidence level and marked in red

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Bloomberg.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Value driver portfolios 30/30 long/short	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT
Annualized excess return	**2.72%**	**1.78%**	**1.37%**	**1.67%**	**1.18%**	**2.60%**	**3.61%**	**3.98%**
Alpha (MKT)	**3.27%**	**1.23%**	**1.51%**	**2.27%**	**2.29%**	**2.93%**	**3.95%**	**5.05%**
t-stat	1.65	0.58	0.74	1.11	1.21	1.39	1.84	2.32
3-factor alpha	**3.97%**	**2.03%**	**2.20%**	**2.96%**	**2.95%**	**3.70%**	**4.74%**	**5.84%**
t-stat	2.23	1.08	1.18	1.60	1.73	1.97	2.49	2.98
MKT beta	**-0.08**	**0.00**	**-0.05**	**-0.09**	**-0.13**	**-0.06**	**-0.08**	**-0.15**
t-stat	-2.04	-0.11	-1.16	-2.11	-3.29	-1.51	-1.74	-3.34
SMB beta	**-0.17**	**-0.10**	**-0.14**	**-0.16**	**-0.19**	**-0.18**	**-0.15**	**-0.14**
t-stat	-2.53	-1.35	-1.97	-2.30	-2.92	-2.58	-2.12	-1.88
HML beta	**0.40**	**0.47**	**0.39**	**0.39**	**0.36**	**0.43**	**0.45**	**0.45**
t-stat	6.46	7.28	6.12	6.12	6.17	6.70	6.91	6.69
Sharpe ratio	**0.36**	**0.22**	**0.17**	**0.21**	**0.16**	**0.32**	**0.44**	**0.47**
Information ratio (3-factor)	**0.52**	**0.25**	**0.28**	**0.38**	**0.41**	**0.46**	**0.58**	**0.70**
Adjusted R^2 (3-factor)	**0.22**	**0.24**	**0.19**	**0.20**	**0.24**	**0.22**	**0.23**	**0.23**

Illustrates the annualized performance of the long/short value driver portfolios and their beta loadings on MKT, SMB, and HML. The portfolios buy the 30% most undervalued stocks and short sell the 30% most overvalued stocks according to their respective valuation model. T-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Bloomberg.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Value driver portfolios Sector exposure	LY ROIC	RONIC = WACC	3Y Median ROIC	5Y Median ROIC	10Y Median ROIC	3Y Average NOPAT	5Y Average NOPAT	10Y Average NOPAT	S&P 500 adj.
Technology	11%	11%	11%	11%	10%	10%	10%	8%	16%
Consumer Cyclical	22%	20%	21%	21%	20%	22%	21%	20%	18%
Healthcare	5%	5%	5%	5%	5%	5%	5%	4%	13%
Energy	9%	14%	9%	9%	9%	10%	10%	10%	8%
Communication Services	1%	1%	1%	1%	1%	1%	1%	1%	3%
Consumer Defensive	17%	7%	17%	18%	18%	17%	16%	15%	10%
Industrials	10%	9%	10%	10%	10%	9%	8%	5%	15%
Basic Materials	5%	6%	5%	4%	4%	5%	5%	4%	6%
Utilities	19%	26%	20%	21%	23%	22%	25%	34%	7%
Real Estate	0%	0%	0%	0%	0%	0%	0%	0%	4%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

Sector exposure of the long-only value driver models. The highest sector exposures are marked in green.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Bloomberg.
Source: Morningstar Direct and own estimations
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09

Appendix 16 - Morningstar Price/Fair Value Decile Fundamentals

Morningstar P/FV deciles Fundamentals	P1 low value	P2	P3	P4	P5	P6	P7	P8	P9	P10 high value	H-L
Book/Market	0.32	0.33	0.46	0.35	0.36	0.37	0.41	0.47	0.56	0.71	0.39
Sales/Market	0.78	0.77	1.43	0.82	0.88	0.92	0.98	1.11	1.40	1.65	0.88
FCFF/EV	2.2%	2.7%	2.8%	2.9%	3.1%	3.1%	3.3%	4.4%	3.9%	5.5%	3.3%
EBITDA/EV	5.8%	8.6%	9.0%	9.6%	10.2%	10.6%	12.1%	12.3%	13.4%	14.3%	8.5%
Earnings/Price	0.4%	3.4%	4.8%	4.4%	4.8%	5.0%	4.7%	5.0%	5.0%	2.4%	2.1%
ROIC	15.9%	19.4%	20.6%	16.7%	13.3%	12.8%	8.4%	15.3%	14.4%	13.5%	-2.4%
EBITDA margin	19.9%	22.1%	22.3%	23.1%	23.2%	23.3%	23.1%	22.9%	21.5%	20.7%	0.8%
EBIT margin	12.7%	15.5%	15.4%	16.2%	16.6%	16.6%	16.1%	15.7%	14.6%	14.5%	1.7%
1Y revenue growth	7.9%	6.9%	6.3%	7.1%	7.6%	7.7%	8.4%	9.2%	9.9%	9.9%	2.0%
NIBD/Equity	0.42	0.54	0.50	0.77	0.81	0.91	0.65	0.38	0.01	-0.32	-0.74

Illustrates the average historical fundamentals and key ratios of Morningstar's price/fair value estimates divided into 10 deciles ranging from high value to low value. Enterprise value is market cap + net interest bearing debt (NIBD). We apply fundamentals from the last fiscal year with a 2-month lag.

Weighting: Equal weighted and monthly rebalancing.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

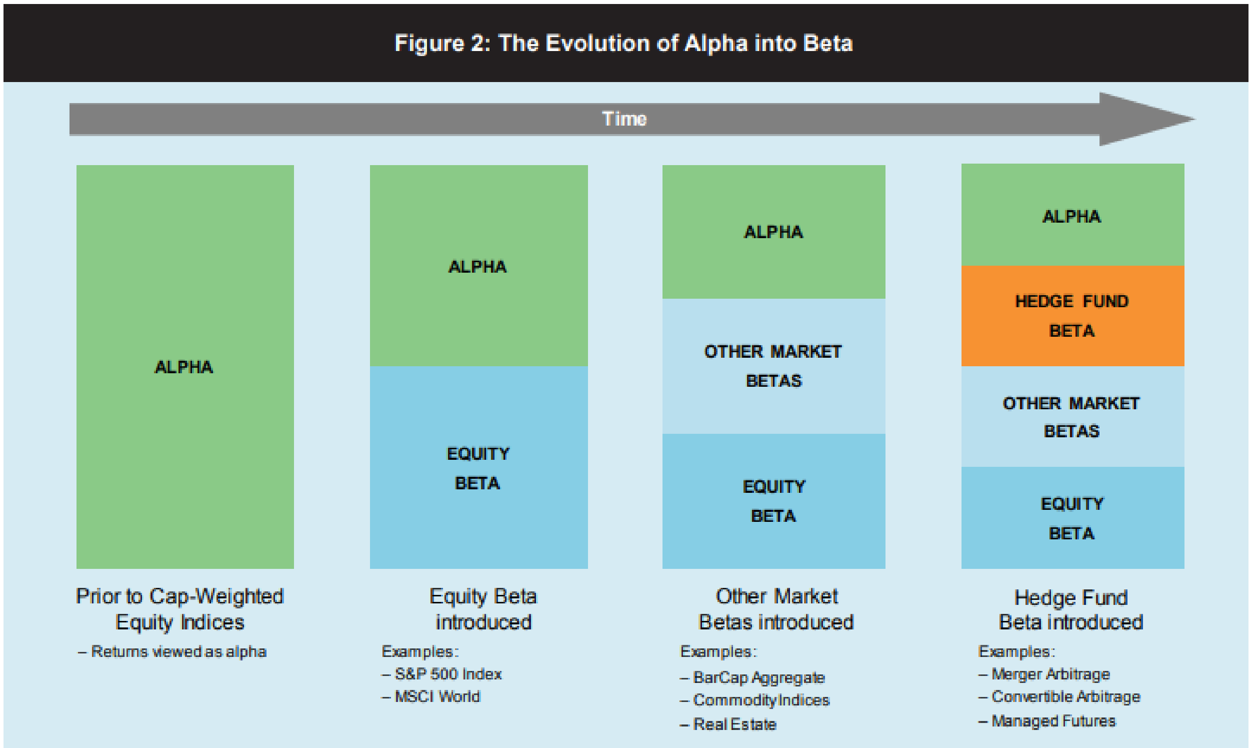
Appendix 17 - Long/Short Morningstar Performance

Morningstar long/short Performance	High-Low	30/30 long/short	1 minus 5 stars
Annualized excess return	**0.2%**	**0.4%**	**12.1%**
t-values	0.05	0.18	1.37
Alpha (MKT)	**-0.9%**	**-1.6%**	**8.1%**
t-values	-0.25	-0.69	0.90
Alpha (S&P 500)	**-0.9%**	**-1.6%**	**8.4%**
t-values	0.28	0.72	2.08
Alpha (S&P 500 ex fin)	**-1.6%**	**-2.1%**	**5.8%**
t-values	-0.45	-0.92	0.65
3-factor alpha (MKT)	**-0.5%**	**-1.3%**	**8.1%**
t-values	-0.15	-0.58	0.90
3-factor alpha (S&P 500 ex fin)	**-1.4%**	**-1.9%**	**6.1%**
t-values	-0.39	-0.86	0.67
Beta (MKT)	**0.10**	**0.19**	**0.39**
t-values	1.37	4.04	2.09
Beta (S&P 500)	**0.11**	**0.20**	**0.38**
t-values	1.42	4.11	1.97
Beta (S&P 500 ex fin)	**0.14**	**0.20**	**0.51**
t-values	2.07	4.56	2.94
Information ratio (MKT)	**-0.06**	**-0.18**	**0.23**
Information ratio (S&P 500)	**-0.07**	**-0.18**	**0.24**
Information ratio (S&P 500 adj.)	**-0.12**	**-0.24**	**0.17**
Adj. R^2 (3-factor MKT)	**0.03**	**0.11**	**0.04**
Annualized volatility	**14.0%**	**9.2%**	**35.0%**
Sharpe ratio	**0.01**	**0.04**	**0.35**

Illustrates the performance of long-short portfolios based on Morningstar's rating for stocks and price/fair value estimates. High - Low (H-L) is long the 10% most undervalued stocks and short the 10% most overvalued. 30/30 long/short is long the 30% most undervalued stocks and short the 30% most overvalued. 1 minus 5 stars is long 1-star stocks and short 5-star stocks. The t-values below 1.96 are insignificant at a 95% confidence level and marked in red.

Weighting: Equal weighted and monthly rebalancing.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 18 - The Evolution from Alpha to Beta



(Cowen, Isreal, Kabiller, Berger, 2012, p. 3)

Appendix 19 - Risk and Return Measures of Portfolios Based on Gordon Growth, the Value Driver Model, and Morningstar's Equity Research

Risk and return measures Long/short portfolios	Excess return	Volatility (Std.)	Sharpe ratio	Alpha (MKT)	Beta (MKT)	Best month	Worst month	Max drawdown	Positive months	Skew	Kurtosis
Gordon Growth portfolios											
LY FCFF	5.6%	6.4%	0.88	4.8%	0.07	9.9%	-4.3%	-14.6%	57.5%	0.8	3.3
3Y Norm FCFF	4.6%	7.5%	0.62	4.2%	0.04	10.5%	-6.0%	-12.5%	60.8%	1.0	4.6
5Y Norm FCFF	3.3%	6.6%	0.51	3.6%	-0.03	6.6%	-6.6%	-13.5%	55.4%	0.1	1.1
10Y Norm FCFF	3.4%	7.4%	0.45	4.1%	-0.07	6.6%	-5.6%	-13.0%	57.0%	0.0	0.6
3Y Average FCFF	6.6%	7.0%	0.94	5.9%	0.06	11.2%	-5.1%	-13.5%	58.1%	0.8	3.5
5Y Average FCFF	3.9%	6.7%	0.58	3.5%	0.03	6.9%	-5.2%	-15.5%	57.0%	0.1	0.4
10Y Average FCFF	4.6%	7.0%	0.66	4.1%	0.05	13.7%	-3.9%	-10.0%	62.4%	1.5	9.5
Value driver portfolios											
LY ROIC	4.0%	7.5%	0.54	3.7%	0.03	12.3%	-5.7%	-19.2%	56.5%	1.0	4.9
RONIC = WACC	3.0%	8.6%	0.35	1.6%	0.14	14.9%	-5.6%	-22.8%	53.8%	1.2	6.3
3Y Median ROIC	2.4%	7.8%	0.31	1.8%	0.06	14.4%	-5.8%	-16.3%	53.8%	1.2	7.8
5Y Median ROIC	2.3%	7.8%	0.30	2.0%	0.03	11.4%	-6.4%	-18.2%	53.8%	0.8	4.3
10Y Median ROIC	2.3%	7.4%	0.31	2.3%	0.00	9.0%	-5.0%	-16.7%	53.2%	0.5	1.9
3Y Average NOPAT	4.2%	8.7%	0.48	3.4%	0.08	17.9%	-4.9%	-13.7%	54.3%	2.1	12.5
5Y Average NOPAT	4.6%	8.7%	0.53	3.7%	0.09	13.2%	-4.6%	-14.6%	54.8%	1.7	6.6
10Y Average NOPAT	5.2%	8.6%	0.61	4.8%	0.04	14.2%	-4.9%	-17.3%	52.7%	1.8	7.0
Morningstar portfolios											
Morningstar H-L	0.2%	14.0%	0.01	-0.9%	0.10	16.2%	-10.1%	-43.6%	49.5%	0.4	1.0
Morningstar L/S	0.4%	9.2%	0.04	-1.6%	0.19	8.7%	-5.7%	-25.5%	48.9%	0.4	0.5
1 minus 5 stars	12.1%	35.0%	0.35	8.1%	0.39	110.5%	-20.7%	-51.1%	52.7%	7.0	74.6
S&P 500 Adj.	12.5%	14.6%	0.86	1.7%	1.05	17.0%	-19.7%	-48.1%	65.6%	-0.5	3.8
Mkt	10.3%	13.6%	0.76	0.0%	1.00	11.4%	-17.2%	-51.5%	66.7%	-0.8	2.4
SMB	2.5%	8.0%	0.31	0.4%	0.21	6.1%	-4.4%	-15.6%	54.3%	0.2	-0.4
HML	0.1%	8.5%	0.01	-1.6%	0.16	8.3%	-11.1%	-32.2%	44.1%	0.0	2.8

Illustrates various risk and return measures for the long/short portfolios based on the Gordon Growth and value driver models. The long/short portfolios buy the 30% of stocks with lowest P/FV and short sell the 30% with highest P/FV. Also includes long/short portfolios based on Morningstar's price/fair value estimates and star ratings, and includes the Fama & French 3-factor models and our equal weighted S&P 500 benchmark excluding financials and duplicates.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Risk and return measures Long-only portfolios	Excess return	Volatility (Std.)	Sharpe ratio	Alpha (MKT)	Beta (MKT)	Best month	Worst month	Max drawdown	Positive months	Skew	Kurtosis
Value driver portfolios											
LY ROIC	13.5%	14.4%	0.94	3.1%	1.01	16.2%	-19.6%	-46.9%	64.5%	-0.6	3.8
RONIC=WACC	14.4%	17.9%	0.80	2.4%	1.16	19.2%	-23.2%	-54.8%	64.0%	-0.5	2.6
3Y Median ROIC	13.4%	14.4%	0.93	3.0%	1.01	16.8%	-19.4%	-47.0%	64.0%	-0.5	3.7
5Y Median ROIC	13.5%	14.3%	0.94	3.1%	1.00	16.4%	-19.0%	-45.5%	62.4%	-0.5	3.5
10Y Median ROIC	12.6%	14.1%	0.89	2.4%	0.98	15.5%	-18.9%	-44.8%	64.5%	-0.5	3.5
3Y Average NOPAT	14.1%	15.0%	0.94	3.5%	1.03	18.1%	-19.5%	-46.2%	62.9%	-0.4	3.6
5Y Average NOPAT	15.0%	15.7%	0.96	4.1%	1.06	18.0%	-19.8%	-42.4%	65.1%	-0.4	3.1
10Y Average NOPAT	17.6%	17.0%	1.03	7.1%	1.01	23.0%	-19.0%	-40.9%	64.5%	0.4	4.0
Gordon Growth portfolios											
LY FCFF	14.5%	14.9%	0.98	3.7%	1.05	16.5%	-19.0%	-45.4%	66.1%	-0.5	3.0
3Y Norm FCFF	14.0%	14.7%	0.95	3.3%	1.04	16.1%	-19.8%	-47.6%	67.2%	-0.6	3.5
5Y Norm FCFF	12.9%	14.3%	0.90	2.4%	1.01	15.2%	-19.4%	-50.1%	66.1%	-0.7	3.6
10Y Norm FCFF	12.9%	14.2%	0.91	2.6%	0.99	15.2%	-19.0%	-49.4%	66.1%	-0.7	3.6
3Y average FCFF	15.5%	15.1%	1.03	4.7%	1.05	17.5%	-19.8%	-44.5%	66.7%	-0.5	3.4
5Y average FCFF	15.5%	15.2%	1.02	4.7%	1.05	17.1%	-19.1%	-42.7%	64.5%	-0.4	3.0
10Y average FCFF	17.3%	17.1%	1.02	6.4%	1.06	20.8%	-19.3%	-44.0%	66.1%	0.1	3.7
Morningstar portfolios											
1 star	21.8%	38.5%	0.57	6.2%	1.52	127.4%	-25.3%	-66.3%	64.5%	7.9	88.8
2 stars	12.2%	16.3%	0.75	1.1%	1.07	18.9%	-22.8%	-62.0%	65.6%	-0.5	5.5
3 stars	11.5%	14.6%	0.79	0.8%	1.04	17.9%	-18.6%	-52.4%	67.2%	-0.6	3.6
4 stars	12.6%	16.2%	0.78	1.2%	1.11	18.5%	-20.0%	-55.3%	60.2%	-0.4	2.9
5 stars	9.7%	20.5%	0.47	-1.9%	1.13	17.8%	-20.9%	-54.8%	59.1%	-0.3	1.8
4 & 5 stars	13.1%	16.1%	0.81	1.8%	1.10	17.6%	-20.5%	-52.2%	62.4%	-0.4	3.0
1 & 2 stars	13.0%	18.1%	0.72	1.0%	1.16	30.1%	-23.7%	-64.0%	64.5%	0.3	8.1
Morningstar P/FV	12.1%	15.3%	0.79	1.0%	1.08	17.5%	-19.8%	-51.4%	61.3%	-0.4	3.4
S&P 500 Adj.	12.5%	14.6%	0.86	1.7%	1.05	17.0%	-19.7%	-48.1%	65.6%	-0.5	3.8
Mkt	10.3%	13.6%	0.76	0.0%	1.00	11.4%	-17.2%	-51.5%	66.7%	-0.8	2.4
SMB	2.5%	8.0%	0.31	0.4%	0.21	6.1%	-4.4%	-15.6%	54.3%	0.2	-0.4
HML	0.1%	8.5%	0.01	-1.6%	0.16	8.3%	-11.1%	-32.2%	44.1%	0.0	2.8

Illustrates various risk and return measures for the long-only portfolios based on the Gordon Growth and value driver models. The long-only portfolios buy the stocks with price/fair value below 1. Also includes long-only portfolios based on Morningstar's price/fair value estimates and star ratings, and includes the Fama & French 3-factor models and our equal weighted S&P 500 benchmark excluding financials and duplicates.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%.
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database and own estimations.
Sample and period: S&P 500 excluding financials and duplicates, 2003.04-2018.09.

Appendix 20 - Gordon Growth Strategies EBIT Stress

Simple investment strategy EBIT stress	**LY FCFF**	**3Y Norm**	**5Y Norm**	**10Y Norm**	**3Y avg.**	**5Y avg.**	**10Y avg.**
Ann. Excess return	14,54%	14,12%	13,14%	13,24%	15,50%	15,53%	17,34%
CAPM alpha	4,91%	4,58%	3,95%	4,12%	5,87%	5,94%	7,61%
t-stat	4,28	3,98	3,76	3,55	4,45	4,20	3,15
3-factor alpha	5,03%	4,65%	4,04%	4,33%	6,02%	6,09%	7,89%
t-stat	4,55	4,11	3,90	3,82	4,73	4,45	3,33
MKT beta	1,00	1,01	0,98	0,97	1,00	0,99	0,99
t-stat	39,76	38,96	41,34	37,51	34,36	31,77	18,28
SMB beta	0,13	0,09	0,07	0,03	0,13	0,14	0,15
t-stat	3,16	2,20	1,87	0,67	2,73	2,68	1,69
HML beta	0,10	0,07	0,07	0,13	0,12	0,13	0,21
t-stat	2,67	1,78	1,99	3,38	2,75	2,69	2,51
Sharpe ratio	0,98	0,95	0,92	0,93	1,03	1,02	1,02
Information ratio (3-factor)	1,14	1,06	1,00	0,97	1,19	1,12	0,85
Adjusted R^2 (3-factor)	94,06%	93,52%	94,37%	92,88%	91,66%	90,15%	73,61%

Performance measures for Gordon's growth strategies with EBIT applied for the normalized investment strategies instead of EBITDA.

Weighting: Equal weighted and monthly rebalancing.
Growth: 3.95%
WACC: Morningstar sector samples.
Source: Morningstar Direct, Kenneth French database, and own estimations.
Market & Period: S&P 500 excluding financials and duplicates, 2003.04 - 2018.09.

Appendix 21 – Formulas for Additional Risk Measures

Drawdown

We calculate the max Drawdown since it is an important risk measure, it is the cumulative loss since losses started.

Drawdowns and Max drawdowns are calculated in the following way:

$$Drawdowns_t = \frac{HWM_t - P_t}{HWM_t}$$

HWM: High Water Mark, highest price (Or highest cumulative return) it has achieved in the past.

P: Stock price

(Pedersen, 2015, p.35).

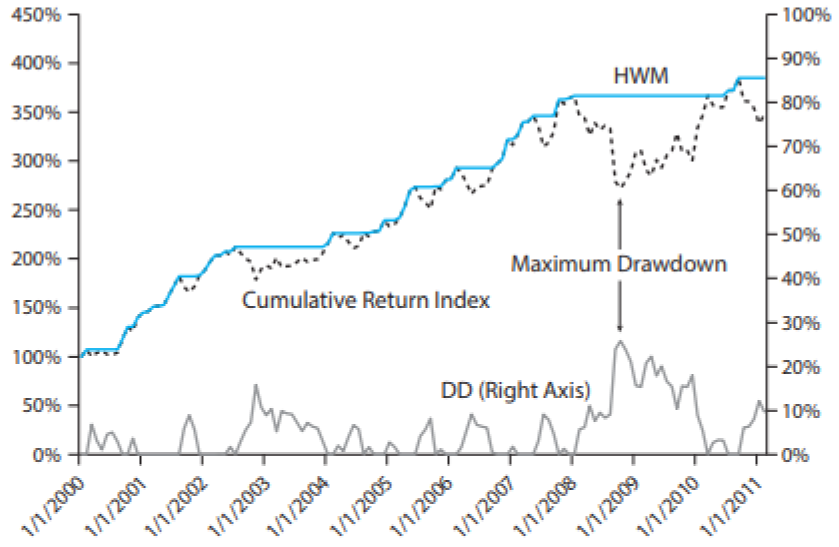


Figure 2.1. A hedge fund strategy's high water mark (HWM) and drawdown (DD).

(Pedersen, 2015, p.36).

Standard deviation

We measure the Standard deviation to understand the volatility of a stock.

Standard deviation of population:

$$\sigma = \sqrt{\frac{\sum_{t=1}^{N}(x_i - \mu)^2}{N}}$$

x: Variable

μ: Average of population

N: Number of observations

Standard deviation of sample test:

$$s = \sqrt{\frac{\sum_{t=1}^{N}(x_i - \bar{x})^2}{N}}$$

x: Variable
$\bar{x}$: Average of sample
N: Number of observations
(Newbold, Carlson, Thorne, 2013, p. 72)

Skewness
If skewness is zero then the distribution is symmetric. A negative skewness means that the distribution is skewed to the left and opposite for positive skewness. This is relevant as a risk measure since we can then see whether the returns is positively or negatively skewed.

$$Skewness = \frac{1}{n} \times \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{s^3}$$

x: Variable
$\bar{x}$: Average of sample
s: Standard deviation of sample
(Newbold, Carlson, Thorne, 2013, p. 91)

Kurtosis
Kurtosis is an important risk measure for hedge funds since it explain the infrequent extreme deviations (outliers). I high kurtosis mean infrequent extreme deviations as opposed to a low kurtosis, which mean that there is frequent modestly sized deviations.

$$Kurtosis = \frac{1}{n} \times \frac{\sum_{i=1}^{n}(x_i - \bar{x})^4}{s^4}$$

x: Variable
$\bar{x}$: Average of sample
s: Standard deviation of sample
(Newbold, Carlson, Thorne, 2013, p. 611)