Realizing Value

Empirical Evidence on Multivariate Fundamental-based Investment Strategies

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Abstract

This thesis examines whether fundamental-based indicators can build the foundation of a zero-cost portfolio strategy that earns statistically significant excess returns. Our empirical analysis can be divided in two steps. First, we separately investigate a wide range of prominent accounting metrics, related to core value investing criteria, on their individual characteristics and predictive ability over future stock returns. We find that gross profits-to-assets, equity-to-assets, current ratio, gross profit growth and book-to-market ratios are best suited to cover these fields. In a second step, we thus build a zero-cost portfolio strategy based on a combination of these five metrics. Such a strategy offers statistically significant average monthly excess returns of 1.26% over the observed sample period (July 1966 to December 2016). The performance analysis displays that observed returns remain largely unexplained by the CAPM and Fama & French (1993, 2015) risk factor models.

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1. Introduction

Following the Efficient Market Hypothesis, stock prices fully incorporate all the best available information instantaneously. Thus, future stock price movements, and consequently returns, should not be possible to be predicted on the basis of historical information. Still, over the years there has been conducted continuous academic work identifying return anomalies that seemingly contradict this hypothesis. Rosenberg, Reid & Lanstein (1985), Fama & French (1992) and Lakonishok, Shleifer & Vishny (1994), among others, find that firms with high book-to-market ratios earn higher future returns than firms with low book-to-market ratios. Banz (1981) finds that stocks of firms with lower market capitalization, on average, offer higher risk-adjusted returns compared to those of companies with larger market capitalization. DeBondt & Thaler (1985, 1987), Jegadeesh (1990) and Jegadeesh & Titman (1993, 2001) find evidence that there are momentum effects in stock returns. Bhandari (1988) argues that future returns on common stock are positively related to a company's leverage, as measured by the debt-to-equity ratio. Contrastingly, Penman, Richardson & Tuna (2007) as well as George & Hwang (2010) find that firms with low leverage generate larger abnormal returns. Ohlson (1980) and Campbell, Hilscher & Szilagyi (2008) find evidence that stocks of companies that exhibit low credit risk outperform those of companies that display strong credit risks. Novy-Marx (2013) documents that, on average, stocks of high profitability firms tend to outperform those of low profitability firms. Whether these anomalies hint at market inefficiencies or are a result of incomplete empirical asset pricing models using suboptimal risk factors to try to explain the expected return cross-section, remains a question. The findings of Hou, Xue & Zhang (2015) show that an enhanced risk factor model can explain roughly 50% of the 80 return anomalies previously perceived to be important, that the authors investigated. However, on the flip-side that also means that at least around 40 return anomalies remain largely unexplained.

Two important questions thus remain: A) Can future stock returns, at least to some extent, be forecasted on the basis of fundamental historic information and B) do investment decisions based on this information relate to efficient risk pricing currently unexplained by empirical asset pricing models or do they instead take advantage of the identification of market mispricing? The paper at hand aims to contribute to an answer for the first question, however we do not set out to formulate new or improved systematic risk factors and thus will also refrain from taking an explicit position towards the question of market efficiency. Instead, the research question this paper sets out to answer is whether there are performance premia in Value Investments, which build on a concept originally introduced by Graham & Dodd (1934). For this paper, we define Value Investing as an investment strategy that is concerned with both the price and the quality of a security. In contrast to Asness, Frazzini & Petersen (2014), who set out to develop a systematic quality-minus-junk (QML) risk factor, we refer to an idiosyncratic stock picking strategy frequently used by practitioners. This is not to be confused with the systematic value risk factor portfolio strategy as discussed, among others, by Fama & French (1993). While the research examining systematic strategies based on independent fundamentals is very extensive, we are confident that we can extend existing empirical research on idiosyncratic stock picking based on a joint analysis of both performance and valuation metrics.

Our literature review identifies two main limitations to the notion of efficient markets. The most striking one is connected to the postulation of rational investor behavior. Instead, as academic research especially in the field of psychology shows, the behavior of an individual is, albeit not necessarily irrational, largely influenced by behavioral biases (see e.g. Barber & Odean (2001), Kahneman & Tversky (1979), Huberman & Regev (2001) and Clarke, Krase & Statman (1994)). Lo (2004) aims to enhance the original Efficient Market Hypothesis with a more evolutionary understanding of individual (and thus investor) behavior and postulates the Adaptive Market Hypothesis. The second important limitation refers to the feasibility of Empirical Asset Pricing Models. While continuously evolving through academic contribution and thus arguably experiencing increased explanatory power over the cross-section of returns over the past decades, to date the existing models remain unable to explain all the observed return anomalies in their entirety. However, as Hou, Xue & Zhang (2015) and Fama & French (2015) argue this could largely be a function of incomplete factor models, suboptimal factor choices and potentially suboptimal factor sorting methods. They believe that with better factor identification more anomalies can be explained and thus there remains a potential for all observed return anomalies to actually refer to currently unidentified systematic factor pricings that are implicitly but effectively conducted by the market participants. The apparent limits of current Empirical Asset Pricing Models are thus not necessarily an indicator for market inefficiency. A lot of the return anomalies are identified by assessing stock price movements against fundamental events. In our literature review we go on to show that academic research found evidence for the ability of fundamental and especially financial statement analysis focused on individual parameters to identify return patterns. While a lot of these patterns are tested against the current Empirical Asset Pricing Models and seem to deliver some statistically significant abnormal returns, they might again relate to the described limitation of Empirical Asset Pricing Models (though behavioral reasons are also often cited and suggested as potential explanations). Whether or not market efficiency is actually existent, our literature review on Fundamental Analysis gives us reason to believe that, at least in the current environment, strategies based on basic accounting fundamentals can earn significant positive expected returns for investors.

Based on these prior academic findings, we start our empirical research with the identification of suitable fundamental signals. We conduct a pre-selection based on popular ratios that mostly have also already been discussed individually by prior research and perform Fama Macbeth regressions to test their predictive ability on future stock returns, both individually and jointly. We then examine whether these perceived signals show persistence over time. Furthermore, we propose univariate portfolio strategies that employ sorts based on the chosen individual metric. Based on this analysis, we identify a set of core metrics representing the main value characteristics of profitability, operational activity, financial stability, growth and inexpensiveness. We find that a combination of metrics consisting of gross profits-to-assets for profitability, equity-to-assets for solvency, current ratio for liquidity, gross profits-to-assets-growth for growth and book-to-market ratio for inexpensiveness as most beneficial for fundamental investors. In a second step, we form portfolios based on these value characteristics, following a z-score weighting approach that has also been used by Asness, Frazzini & Pedersen (2014). For our portfolio formation, we weight our five indicator measures according to their predictive ability with a weighting scheme giving a weight of 40% to the book-to-market ratio, 30% to the gross profits-to-assets ratio, 7.5% to the equity-to-assets ratio, 7.5% to the current ratio and 15% to the gross profits-growth ratio. This should resemble a typical value investing strategy, placing strong importance on inexpensiveness and profitability, with the other ratios acting as supplementary decision criteria. These portfolios are rebalanced every year. We find that such a portfolio formation strategy, especially if used to derive a zero-cost portfolio H-L going long the highest value characteristic portfolio and short the lowest value characteristic portfolio, offers large and statistically significant excess and abnormal returns, even over the Fama & French (2015) five-factor model which incorporates profitability. We go on to show that our findings are robust for different weighting schemes and rebalancing intervals, as well as over different subsample periods. We also find general robustness in regards to size, though excess and abnormal returns are more statistically significant for firms with small market capitalizations and somewhat less so for mid and large size market capitalizations. We thus extend the findings of Novy-Marx (2013), Fama & French (2015) and Hoe, Xue & Zhang (2015), among others, and underline those of Asness, Frazzini & Pedersen (2014), by showing that future stock returns are not only related to size, profitability and investments, but apparently also to further value characteristics like solvency, liquidity and growth. We also extend the majority of research conducted about the predictive ability of fundamental signals by offering a way to directly combine these fundamental signals and test their joint predictive ability, in contrast to the apparently most pronounced current methods of academic assessment that usually has researchers focus only on individual fundamental signals or a combination of a limited number of fundamental signals at best. This should also further aid practitioners in their portfolio design processes.

The further structure of this paper is as follows: In Section 2 we briefly introduce the three academic research areas most closely related to our paper, namely Market Efficiency & Behavioral Finance, Empirical Asset Pricing and The Value Investing Strategy & Fundamental Analysis. We will give an overview over existing literature and describe how we intend to contribute to mentioned fields. Section 3 will first describe the data and methodology used, then move on to describe and analyze the results of our regression analysis. In a last step, it will evaluate the robustness of our empirical approach, focusing on some identified core areas. Section 4 concludes. Tables are presented separately in Section 5 and in the Appendix. Figures are displayed in Section 6. Section 7 lists references.

2. Literature review

Our paper fits in with the following research areas: Market Efficiency & Behavioral Finance, Empirical Asset Pricing, and Value Investing & Fundamental Analysis. For the reader to gain a fundamental understanding of these research areas, we will over the following paragraphs introduce each of these research areas, as well as core bodies of academic work and discuss their main arguments to embody the findings of our thesis into a broader academic perspective. First, we will recapitulate the notion of market efficiency, observed violations of it, and the consequent critique brought forward from empirical asset pricing and behavioral finance. We will also briefly introduce how the adaptive market hypothesis aims at providing a framework to combine both schools of thought. Second, we will introduce core work in the area of Empirical Asset Pricing and provide a brief overview of some core methodologies which build the foundation for our own empirical research. Third, we will define the Value Investing Strategy as well as the area of Fundamental Analysis. We will provide academic evidence on the ability of fundamental analysis to forecast changes in asset prices and provide insights in academic research discussing the ability of its core components to enhance investment decision making.

2.1 Market Efficiency and Behavioral Finance

2.1.1 The Efficient Market Hypothesis

The question of whether or not markets are efficient, and if so to what degree, is likely among the most discussed and controversial in academic finance. The Efficient Market Hypothesis, as formulated by Roberts (1967) and Fama (1970), remains one of the most influential ideas in finance to date. It postulates the notion that speculative asset prices always incorporate the best available information about fundamental (intrinsic) asset values instantaneously and only change due to the introduction of new information. It arguably builds on the work of Samuelson (1965), who designed a stochastic model in order to show that price changes exhibit martingale properties, meaning that future price changes are uncorrelated with past price changes and expected capital gains equal zero. Subsequently, Fama (1970) provided a summary of academic research on the Efficient Market Hypothesis in a review article and formed the conclusion that stock markets can generally be perceived as efficient, albeit with some exceptions. He largely based this finding on tests of return autocorrelations for daily and weekly frequencies, and perceived this observation to hold for both, individual stocks and stock markets as a whole. Consequently, the popular believe at the time was that stock picking strategies should not be able to provide higher risk-adjusted returns than investment strategies that incorporate random stock selection, independent of whether they focus on historical return patterns or fundamental analysis respectively.

The concept of efficient markets also largely builds on Samuelson's (1947) theory of the individual consumer, which postulates that individuals aim to maximize their expected utility functions while exhibiting rational expectations. Building on this concept, Lucas (1978) argued that, in a general equilibrium based on rational expectations, rational asset prices might inhibit a forecastable element related to the forecastability of consumption. The Efficient Market Hypothesis is furthermore strongly connected with the notion of stock prices following a so-called random walk, meaning that future price changes of financial assets are unpredictable and uncorrelated to each other. The Random Walk Hypothesis was famously discussed by Malkiel (1973) who argued that investors cannot consistently outperform the market portfolio through individual stock picking, but ultimately goes back to Bachelier (1900) (Fama, 1970). It is also seen as a foundation of thought for the Capital Asset Pricing Model (CAPM) as introduced by Sharpe (1964) and Lintner (1965).

Importantly, while arguing for the Efficient Market Hypothesis to hold in general, as it fits fairly well to the data he obtained, Fama (1970) disclosed his perception that it represents an extreme null hypothesis and thus cannot be expected to be literally true. Indeed both, the notion of efficient markets and random walks, and the CAPM have subsequently come under increased scrutiny, evoking skepticism and criticism from an empirical asset pricing and a behavioral finance perspective.

2.1.2 Empirical Criticism

The Random Walk Hypothesis has encountered strong rejection by Lo and MacKinlay (1988). The authors conducted tests on weekly return data for indices as well as size-sorted stock portfolios and individual stocks. Throughout their tests, they identified significant positive serial correlation among stock returns, therefore countering the notion of future price changes being uncorrelated.

The CAPM has been critiqued by numerous researchers over the years. For example, Basu (1977) reports that he finds portfolios of NYSE traded stocks with high earnings yield average higher absolute, as well as risk-adjusted, returns than portfolios with randomly selected constituents. Banz (1981) investigates the performance of NYSE traded firms and reports a size effect on observed risk-adjusted returns, with small firms earning higher returns than large ones over a 40-year period. According to him, this hints at a CAPM misspecification. Basu (1983) finds that high E/P firms average higher risk-adjusted returns on their common stock than low E/P firms, even after controls for firm size have been implemented. However, he reports that the size effect previously identified by Banz (1981) largely disappears when returns are controlled for E/P ratio and risk discrepancies among investigated stocks. Still, he also reports evidence that there is some interdependency between E/P effect and size. Ang & Chen (2005) argue that, while the original CAPM could not explain the book-to-market effect (high book-to-market firms on average demanding positive excess returns compared to low book-to-market firms), with a conditional CAPM, incorporating time-varying betas, predictable market risk premia and stochastic systemic volatility, little evidence for excess returns different from zero can be found.

Furthermore, already in his postulation of the Efficient Market Hypothesis, Fama (1970) himself reported return anomalies, like serial dependencies in stock market returns, though he pointed out that those were only minor in nature. Shiller (1981) and LeRoy & Porter (1981) found excess volatility in the aggregate stock market relative to the present value of the stock market as implied by the efficient markets model. For further consideration, a detailed overview of major anomalies and a discussion of the corresponding evidence for them is provided by Siegel & Coxe (2002).

However, while the Random Walk Hypothesis and the original CAPM can be perceived to be rejected, the same does not necessarily hold true for the Efficient Market Hypothesis or the usefulness of multi-factor asset pricing models in general. Instead, it remains a likely possibility that current Empirical Asset Pricing models are simply incomplete. As such, the fact that they are unable to attribute identified excess returns to systematic risk factors might purely be a result of imperfect factor calibration (Hou, Xue and Zhang, 2015) and/ or subpar factor sorting methods (Fama and French, 2015), which, if solved more efficiently, could potentially better explain or even eliminate perceived return anomalies entirely. We will further discuss this notion in the paragraphs focusing on Empirical Asset Pricing.

2.1.3 Behavioral Criticism

One of the early behavioral criticisms of the efficient market hypothesis counters Samuelson's (1947) theory of the individual customer. Simon's (1955) theory of "satisficing" claims that humans are constraint in their computational abilities and thus settle for satisfactory instead of optimal optimizations, which impedes the notion of rationally optimal choice.

However, Simon's (1955) notion has subsequently been criticized in economics for the lack of specific determinants that prompt individuals to stop optimizing and reach merely satisfactory decisions. Lo (2004) finds that evolutionary theory can enhance Simon's (1955) theory, claiming that the necessary determination results through trial and error and thus, in a way, natural selection, as well as through the environment that drives these selection processes. This claim relates to Dawkins (1976) postulation that individuals are organisms which have been taught to maximize the survival of their genetic material. As individuals learn from positive reinforcement of past decisions, they develop heuristics with which they engage future decision making challenges. These heuristics are susceptible to changes of the (economic) environment as behavioral rules based on past observations of favorable outcomes to specific conduct might be unsuitable in changed circumstances, thus creating behavioral biases undermining decision making performance. However, as Lo (2004) states, these biases, while resulting in suboptimal behavior, cannot be regarded as irrational but rather as maladaptive.

Behavioral biases like overreaction, overconfidence and confirmation bias are often cited by academic literature to explain observed return anomalies. See for example DeBondt & Thaler (1985), who argue that they find evidence for investor overreaction to unexpected new events, leading portfolios of past ‘losers’ to offer higher risk-adjusted returns than portfolios of past ‘winners’.

2.1.4 The Adaptive Market Hypothesis

Combining the efficient-market hypothesis with evolutionary principles, the adaptive market hypothesis postulates that asset prices reflect information in a way that is dictated by a combination of environmental conditions and the number of value systems formed by distinct groups of market participants. Lo (2004) further proclaims that a market’s efficiency depends on the number of separate distinct groups competing for resources, as well as on the scarcity of such. Multiple groups competing for scarce resources will yield pricing that is incorporating and reflecting information in a more absolute and immediate manner than a scenario where a limited number of groups competes for abundant resources. Consequently, he regards the level of market efficiency as highly contextual and dynamic. “Therefore, under the [adaptive market hypothesis], investment strategies undergo cycles of profitability and loss in response to changing business conditions, the number of competitors entering and exiting the industry, and the type and magnitude of profit opportunities available” (Lo, 2004).

Several implications arise from the adaptive markets hypothesis. For one, the relation between risk and reward is determined by the relative sizes and preferences of different investor groups active in each market, as well as on regulatory and tax considerations. Therefore, the mentioned relation is likely to be dynamic and will shift over time. This will lead to fluctuations in asset risk premia and consequently in asset prices. Secondly, the adaptive market hypothesis gives, in contrast to the Efficient Market Hypothesis, room for arbitrage opportunities to exist. Here, Lo (2004) points at Grossman & Stiglitz (1980) who argue that in a world without such opportunities the price-discovery aspect of financial markets will collapse, given that there is no incentive to gather additional information about underlying asset values. Furthermore, the adaptive market hypothesis implies that due to the dynamic of market participation and changing composition of the population of market participants, new arbitrage opportunities will constantly be created. Thirdly, with changes in market and investment environments, investment strategies alike should be viewed as dynamic and might experience decline in profitability which, again in contrast to the

Efficient Market Hypothesis, might be recovered in later stages, if the majority of the investment population move to differing strategies to enhance short-term returns, allowing profitability recovery in the long-run. Lastly, the adaptive market hypothesis implies that “innovation is key to survival”. (Lo, 2004) With shifting investor preferences and subsequently risk-reward relations, achieving constant levels of expected returns demands adaptation to changing conditions of the financial markets and the real economy.

2.2 Empirical Asset Pricing

Over the following paragraphs, we will briefly describe the three-factor model proposed by Fama & French (1992, 1993), some popular four-factor enhancement proposals and finally the five-factor model of Fama & French (2015), as well as corresponding underlying anomalies in expected stock returns that they set out to explain. We will conclude this section with a short discussion about the perceived limits to empirical asset pricing.

2.2.1 The Three Factor Model

Fama & French (1992, 1993) argue that the cross-section of common stock returns in the U.S. market exhibit limited relation to the CAPM market risk factor of Sharpe (1964) and Lintner (1965), and the consumption beta as discussed by Breeden (1979). Instead, they find that average return cross-sections can be more reliably explained by other variables, most importantly size measured by a stocks market capitalization, earnings-to-price and book-to-market ratios, as well as leverage. On the basis of this observation, Fama & French (1993) construct a model focused on five common risk factors for stocks and bonds. For this paper, we will only focus on the risk factors relating to stocks, as the authors show that the two bond risk factors display little explanatory power over average excess returns on common stocks. The model constructed by the authors uses a market risk factor, as well as a size (market capitalization) and a value factor (book-to-market ratio).

The market risk factor (RMO) relates average returns to the systematic risk an investor is exposed to, essentially measuring the probability of gains and losses based on the overall performance of the financial market in consideration. Systematic risk arising from sources like natural disasters, interest rate changes, and recessions, can per definition not be diversified but only hedged against. The higher the systematic risk an asset is exposed to, the higher should be the market excess return, measured as the orthogonalized market return over risk-free return (approximated by the treasury yield). The authors find that the RMO factor relates to an average monthly return of 0.50% in all their observed stock portfolios, labeling it a common part of stocks average excess returns.

The size factor, also reference as SMB (small-minus-big) centers around the observation that smaller sized firms offer higher expected returns than larger firms. Fama and French (1993) relate this to economic fundamentals, specifically a company's profitability. The authors show that small firms experience lower earnings on assets than big firms, an effect that is especially magnified during recession periods, namely the time between 1980 and 1982. This susceptibility to earnings depression, according to the authors, can be associated with a common risk factor explaining a negative correlation between size and average returns.

The value factor, referenced as HML (high-minus-low) is based on the observation that company stocks with high book-to-market ratios exhibit a tendency to offer lower earnings on assets which persist for the period of five years prior and past the book-to-market measurement. According to the authors, this relation suggests that relative profitability acts as source for a common risk factor explaining the negative relation between book-to-market ratios and average stock returns.

Fama & French (1993) believe that the usage of these factors enables the explanation of common stock return variations and the cross-section of average returns. However, they state that while the observed descriptive ability can be labeled as good, it does not require that the authors identified the true factors. Subsequent research shows that the descriptive ability of the three-factor model is indeed restricted and can consequently be enhanced by the introduction of new factors.

2.2.2 Selected Additional Alternative Systematic Risk Factors

Jegadeesh & Titman (1993) found that an investment strategy focused on buying stocks with positive performance in the past while simultaneously shorting stocks that have performed negatively over the same period results in significant positive excess returns over a 3-12 month holding period which are unexplained by the common risk factors utilized by the Fama and French (1993) three-factor model and subsequently coined as momentum anomaly. Carhart (1997) goes on to demonstrate that a four-factor model including a factor for momentum can capture this anomaly. His PR1YR factor relates to portfolios constructed as equally weighted average of companies with the highest 30% eleven-month returns minus the corresponding lowest 30% eleven-month return firms, lagged by one month.

Pástor & Stambaugh (2003) show that expected returns display cross-sectional links to return sensitivities of aggregated market liquidity fluctuations. They report that portfolios constructed going long stocks with high liquidity sensitivity and simultaneously shorting stocks with low liquidity sensitivity earn excess returns of 7.5% per annum over a 34-year period. They develop a model for stock liquidity betas and introduce a liquidity factor, LIQ.

Asness, Frazzini & Pedersen (2014) argue that stocks exhibiting high quality characteristics, measured in regards to safety, profitability, growth, and payout ratios, should on average demand higher prices than those falling short of these characteristics. They construct a quality-minus-junk (QML) factor and identify that portfolios long quality and short junk stocks earns significant risk-adjusted returns in the financial markets of 25 countries globally. However, they argue that they are unable to explicitly tie this observation to risk and argue that their findings potentially rather relate to a mispricing anomaly.

Hou, Xue & Zhang (2015) develop a factor model enhancing the Fama & French (1993) three-factor model with an investment (measured by Investment-to-assets, the annual change in total assets divided by prior year's total assets) and a profitability factor (measured by return on equity, ROE). They further use this enhanced factor model to examine a set of approximately 80 reported anomalies and find that close to half of these anomalies are insignificant when examined with their model, with the rest of the anomalies significantly better captured than through the Fama & French (1993) three-factor model or Carhart's (1997) four-factor model.

2.2.3 The Five Factor Model

In line with the findings of Hou, Xue & Zhang (2015), Fama & French (2015) find that a five-factor model incorporating patterns regarding size (SMB), value (HML), profitability (RMW), and investment (CMA) has significantly more predictive power over average stock returns than their three-factor model. However, they argue that it experiences challenges regarding the explanation of low average stock returns on small firms. They also find that the introduction of profitability and investment factors renders the value factor as redundant, at least for the sample they examine.

They decided to include profitability and investment factors due to academic evidence showing that those characteristics add to the average return description provided by the book-to-market ratio, referring to the findings of Novy-Marx (2013) and Aharoni, Grundy, & Zeng (2013), among others. They find the book-to-market ratio in itself to be a noisy predictor of expected returns, as a company's market capitalization is responsive of forecasted earnings and investments. In order to reduce this impact, Fama & French (2015) construct the robust-minus-weak (profitability) factor (RMW), representing a diversified stock portfolio long robust profitability and short weak profitability stocks. Additionally, they construct a conservative-minus-aggressive (CMA) investment portfolio, representing the difference in returns between stocks of companies with low and high investment commitments. While they find that this enhanced factor model is still rejected by the test proposed from Gibbons, Ross & Shanken (1989, briefly explained in the following section), the authors estimate that it can explain between 71 and 94% of the expected returns cross-section variance for the examined portfolios. As stated before, the main challenge for the model is attributed to small firms with negative factor exposure to RMW and CMA.

2.2.4 Limits of Empirical Asset Pricing Models

McLean & Pontiff (2016) study the ability of 97 characteristics aimed at the explanation of cross-sectional returns and find that the average return of a cross-sectional predictor declines by 58% post publication, arguing that most of the perceived cross-sectional predictability emanate from mispricing and that investors learn about such mispricing through academic publications. Following Campbell & Cochrane (1999) who postulate that predictability is likely to persist if it accurately reflects risk, these findings go against the inherent claim of empirical asset pricing models that predictability of returns relates exclusively to rational expectations.

Gibbons, Ross & Shanken (1989) develop a test of the efficiency of portfolios, based on multivariate statistical methods. As Fama & French (2015) state, this test assesses whether empirical models can provide complete descriptions of expected returns. To our knowledge, none of the individual systematic risk factors, nor any of the factor combining empirical asset pricing models, could pass this test, rendering their explanatory ability as limited at best. However, Hou, Xue & Zhang (2015), and Fama & French (2015) show that a conscious factor choice and combination can indeed increase the models explanatory ability and eliminate numerous of the perceivably observed return anomalies identified by academia. The right factor sorting method might also enhance a model's predictive ability, though Fama & French (2015) argue that, in their analysis, the choice appears largely inconsequential. Still, Fama & French (2015) also argue that a model's ability to predict returns is likely most efficient with combinations of four to five factors, as the introduction of every additional factor potentially drives up correlations that could result in subpar diversification of at least some portfolios.

Finally, it seems important to keep in mind that models in general and scientific models in particular represent approximations and thus simplified versions of reality (Box & Draper, 1987). Consequently, every claim or expectation that an empirical asset pricing model can predict expected returns in their entirety likely should be seen as a stretch.

2.3 The Value Investing Strategy and Fundamental Analysis

2.3.1 The Value Investing Strategy

Value Investing as an investment paradigm goes back to Graham & Dodd (1934). It mainly postulates the idea of buying financial assets for which fundamental analysis hints at an underpricing by the market. As Lakonishok, Shleifer & Vishny (1994) report, a core component of value investing strategies is buying securities that exhibit low market prices when compared to earnings, dividends, book values or comparable value measures. Basu (1977) finds that for the period from 1957 to 1971 low Price/Earnings ratio (P/E) portfolios earned on average higher risk-adjusted returns than portfolios constructed with high P/E securities. Stattman (1980) and Rosenberg, Reid & Lanstein (1985) show a positive relation between book-to-market values and average U.S. stock returns. Chan, Hamao & Lakonishok (1991) examine cross-sectional return differences of Japanese stocks in relation to the development of underlying fundamental variables over the period between 1971 and 1988. The examined fundamental variables consist of earnings yield, size, the book-to-market ratio and cash flow yield. The authors claim a significant relation among expected returns and fundamental variables for the Japanese market, with the book-to-market ratio and cash flow yield exhibiting the strongest impact.

As discussed in the Empirical Asset Pricing section, Fama & French (1993) relate higher expected returns for value stocks in comparison to growth stocks mainly to a larger loading of the systematic value risk factor. In contrast, a Value Investing Strategy does not necessarily focus on systematic risks. Prominent variants of the Value Investing Strategy can be described as largely contrarian, focused on idiosyncratic risk assessments for individual underlyings. These idiosyncratic risks are investigated through the use of Fundamental Analysis and benefit the identification of an asset's intrinsic value. This intrinsic value is afterwards compared to the currently prevailing market price of the asset and an investment decision is made if the market price is below (or in some cases at) the asset's perceived intrinsic value. While, according to Fama & French (1993), risk-adjusted returns for value and growth firms should be largely aligned, Lakonishok, Shleifer & Vishny (1994) show that value stocks have outperformed growth stocks, even though they did not find evidence that value stocks exhibit larger levels of fundamental risk that could explain higher levels of average returns. Instead, the authors relate their finding mostly to mispricing, resulting from behavioral biases cumulating in judgement errors. This supports the claim that idiosyncratic risk identification through fundamental analysis can enable excess returns for fundamental value investing strategies.

2.3.2 Fundamental Analysis

Fundamental analysts aim at establishing a guidance on the intrinsic value of financial instruments through the gathering, processing and interpretation of publicly available information. This intrinsic value estimate is obtained by a combination of the following main types of data sources: financial statements, market data and economic data. Importantly, Fundamental Analysis combines both the assessment of financial (core) ratios and qualitative data, contrary to the popular believe that largely equates fundamental analysis purely with financial statement analysis (though financial statement analysis also functions as a strong driver for the qualitative analysis). A combination of these data sources should provide for an accurate assessment of a company's current and future financial condition. This assessment then leads to an estimate of the net present value of expected future earnings, which consequently depends on analysts' earnings forecasts (Abarbanell & Bushee, 1998).

Academic research shows that Fundamental Analysis indeed inhibits the ability to yield significant excess returns. Bernard & Thomas (1989) find that evidence that the observed post-earnings-announcement drift in stock returns relates to delayed price response to earnings surprises. Ou & Penman (1989) as well conclude that market prices fall short of an accurate reflection of financial statement data which the authors deem practical to indicate future earnings reversals. Sloan (1996) dissects current earnings to investigate whether information relating to future earnings development contained in their cash flow and accrual components is accurately reflected by stock prices. He finds evidence that investors inhibit a fixation on the accumulated earnings positions alone and tend to ignore, at least in part, incremental information about accruals and cash flows that impact future earnings. Both these findings reflect the notion that fundamental analysis can enable returns, especially around earnings announcement dates.

Abarbarnell & Bushee (1998) form portfolios based on a variety of signals, largely focused on working capital and gross profitability, as well as capital expenditures and effective tax rates. They show that these portfolios earn, after size-adjustments, an average cumulative 12-month abnormal return of 13.2%.

Fairfield & Whisenant (2001) find evidence supporting the claim that Fundamental Analysis can be used to forecast deteriorating operational firm performance, even if masked by aggressive accounting. They use a sample of 373 firms which have been assessed by the Center for Financial Research and Analysis (CFRA) over a four-year period. The CFRA provides investors with monthly reports that pinpoint around ten companies each who, according to the CFRA, experience problems in their underlying operating business with additional focus on such that attempt to cover those through unusual or aggressive accounting methods. The authors record significant negative abnormal returns for stocks whose underlying companies have been identified and reported by the CFRA. These post-event negative abnormal returns are followed by a statistically significant deterioration in financial performance in the year after the recommendations, evident from changes in earnings per share, returns on assets and profit margins.

2.3.2.1 Financial Ratio Analysis

In the following paragraphs, we will distinguish subsets of financial ratio analysis. According to the CFA Institute (Clayman, Fridson & Troughton, 2012), Financial Statement Analysis groups financial core ratios in four groups: Profitability, Liquidity, Solvency and Activity. In Addition, we will consider related valuation ratios. Finally, we set out to briefly describe some core components of qualitative fundamental analysis. We will show whether academia found these variables in itself able to observably enhance the quality of investment choices. Importantly, the following discussion is in no way meant to be exhaustive, as the sheer range of qualitative factors and quantitative ratios that can and often are included in fundamental analysis is simply too wide for a holistic assessment of each individual metric to fit in the scope of this paper.

2.3.2.1.1 Fundamental Ratios: Profitability, Activity, Solvency & Liquidity

Profitability ratios assess a company's ability to manage expenses in a way that enables it to generate profits from its sales. They are further divided into margins and return ratios. The most prominent margins are the gross profit, operating profit and net profit margins, relating different types of accounting profits to a company's revenues. Return ratios compare the achieved profits with the necessary investment to enable and realize projects. The most prominent return ratios include operating return on assets, return on assets, return on total capital, return on equity and return on capital employed. Detailed descriptions of the margin and ratio components are provided by Clayman, Fridson & Troughton (2012).

According to the authors, activity ratios display a company's effectiveness in regards to the usage of its working capital investments. As such, the most prominent ratios include inventory turnover, receivable turnover and total asset turnover. These ratios also build the foundation of a firm's operating cycle assessment. The operating cycle assessment culminates into the cash conversion cycle, which expresses the period length between cash outflows driven by the purchase of resource inputs and cash inflows from the sale of a finished product to the firm's customers. Profitability and activity ratios are connected, as shown through the DuPont formulas, who decompose the return ratios into products of margins and asset turnover.

Solvency ratios signal an entity's ability to meet its debt obligations and as such indicate the level of financial risk it is exposed to. They are further distinguished into leverage and coverage ratios. Leverage ratios provide information about a company's capital structure and potential refinancing risks. The most prominent leverage ratios include the (net-) debt-to-equity, (net-) debt-to-capital and solvency ratio, as well as the cash-flow-to-debt ratio. Coverage ratios have a stronger cash flow focus and signal an entity's ability to continuously comply with its interest payment obligations. They include the interest coverage ratio and the cash flow coverage ratio (Clayman, Fridson & Troughton, 2012).

Liquidity ratios assess a company's ability to meet its short-term obligations, mostly through the usage of cash and the conversion of assets that are interpreted as cash-equivalent due to them exhibiting characteristics that enable close-to-immediate cash conversion (liquidation without penalization). The most prominent liquidity ratios are the current, quick and cash ratios (Clayman, Fridson & Troughton, 2012). Alternative measures include the cash-to-sales ratio, dividing and company's cash and cash equivalents by its sales.

Shin & Soenen (1998) examine the impact of a firm's cash conversion cycle on its profitability. Covering 58,985 companies over the period from 1975 to 1994 they identify a strong negative correlation between the two. Furthermore, they find that shorter cash conversion cycles can be associated with higher risk-adjusted equity returns.

Nissim & Ziv (2001) enquire into the relation between changes in dividends and future firm profitability. The authors discover that dividend changes promote incremental information about a company's future profitability and identify a positive relation between dividend changes and earnings development over the period of the two subsequent years.

Eberhart, Maxwell & Siddique (2004) locate significant positive abnormal returns for companies that show surprise increases in R&D expenditures. They furthermore discover evidence showing that sample firms incorporating significant R&D expenditure increases experience strong positive long-term operating performance increases. As such, the authors argue that, while R&D expenditures constitute beneficial investments for future shareholder wealth generation, the market appears to be slow to recognize their impact. Consequently, the improved operating performance following the increase in R&D expense can be interpreted as a signaling channel to the market.

Martani & Khairurizka (2009) also find that a firm's profitability, turnover and market value have significant impact on the expected stock return.

Finally, as discussed in the Empirical Asset Pricing section, Asness, Frazzini & Pedersen (2014) show that a portfolio long quality stocks and short junk stocks achieves significant risk-adjusted returns in 25 different financial markets. The authors define the quality of a stock based on four characteristics: Profitability, growth, safety and payout. While they find that higher quality exhibits a significant association with higher prices, they state that the overall explanatory power of quality on price appears limited. The authors discover a positive correlation between the characteristics profitability and growth, and stock price. Surprisingly, they also discover a mixed and sometimes negative association between the safety characteristic and stock prices, while payout displays a negative correlation.

2.3.2.1.2 Valuation Ratios

The value investing strategy incorporates valuation ratios, first and foremost to assess whether the asset in consideration can be considered as inexpensive relative to its intrinsic value. In addition, the analysis of historical valuation ratios might provide insights into a company's financing strategy (covered in more detail in the qualitative analysis section) and arguably has some power over the prediction of future returns.

DeBondt & Thaler (1985) show that portfolios formed of past 'losers', companies that experienced extreme capital losses over a period of up to five years, outperform 'winner' portfolios (those companies that experienced extreme capital gains correspondingly). Three years after the portfolio formation, the authors report positive cumulative returns of 25%, while deeming the 'winner' portfolio as significantly riskier. They interpret their findings as consistent with the overreaction hypothesis. Zarowin (1990) instead claims that the observed tendency of past 'losers' to outperform 'winners' is not due to overreaction but rather a result of discrepancy in firm size among the two groups. He finds that the core driver for 'loser' outperformance is a tendency of 'losers' to be smaller in capitalization than 'winners' and finds little evidence for return anomalies among size adjusted portfolios. Furthermore, he documents that for 'winner' portfolios whose constituents are smaller in size than the constituents of the corresponding 'loser' portfolio, 'winners' tend to outperform instead.

Chopra, Lakonishok and Ritter (1992) also report that extreme prior 'losers' tend to outperform 'winners'. They form portfolios based on returns of the five years prior to formation and hold these for five years. With that, they identify 'loser' outperformance of 5-10% per annum, with the magnitude of the effect being stronger for smaller firms than for larger.

Contrasting to DeBondt & Thaler (1985) and Chopra, Lakonishok & Ritter (1992), Jegadeesh & Titman (1993) apply a trading strategy that goes long past 'winners' and short past 'losers', and report significant abnormal returns over the period between 1965 and 1989. However, they also report that most of the achieved excess returns of the 'winner' portfolio is achieved in the beginning of the holding period, with the 'losers' actually providing significantly higher returns than the 'winners' over the period between 8 to 20 months after portfolio formation. The discrepancy between these studies can therefore likely be a function of holding periods and/ or assessment periods of winning/ losing characteristics prior to portfolio formation.

Lewellen (2004) examines the predictive ability of financial ratios; mainly dividend yield, book-to-market ratio and earnings-price ratio; on aggregate stock returns. He shows that mentioned ratios indeed act as predictors of market returns during the period of 1963-2000 (1946-2000 for dividend yield). The author's findings contrast prior academic research stating that most of the perceived predictive power originates from small-sample bias. Lewellen (2004) criticizes this notion, stating that a focus on the marginal distribution of the predictive slope tends to ignore potentially useful information if the autocorrelation of chosen predictive variables is close to 1 and thus is prone to understate the significance of closely related variables like the three in consideration.

2.3.2.2 Qualitative Analysis

The qualitative aspects of fundamental analysis largely center on implications of strategic initiatives for the future of a company's stock performance; as well as the field of corporate governance, the resulting incentives for companies and their managements to act according to shareholder interests and consequently the overall shareholder friendliness of individual companies.

2.3.2.2.1 Strategic Initiatives

Strategic initiatives are largely focused on the assessment of growth channels, the company's product mix and its optimal capital structure. Consequently, both are essentially investment decisions, affecting the balance sheet through capital issuance/ repurchases and acquisitions/ asset sales.

Ikenberry, Lakonishok & Vermaelen (1995) examine the impact of share repurchase announcements on future stock performance, over the 10-year period starting 1980. For buy-and-hold investors with an investment span of four years, they identify abnormal returns after the announcement date of 12.1%. Moreover, they take a specific look at value stocks, which they argue to be more likely to repurchase shares due to undervaluation, and find average excess returns of 45.3% for this subgroup of companies. They thus conclude that the market underreacts to and potentially ignores information inherent in repurchase announcements.

Loughran & Ritter (1995) find that, for the 20-year period starting 1970, equity issuing firms significantly underperform companies that do not issue additional equity. They report that firms conducting an IPO average returns of 5% per year, compared to 12% for matching non-issuing firms. For SEOs, they report average returns after issuance of 8% per annum, compared to 15% for matching non-issuing firms. The authors largely attribute the findings concerning IPOs to overvaluation resulting from overestimation of growth potentials. For SEOs, the authors' interpretation again centers on overvaluation, combined with the market's apparent inability to revalue the stock correspondingly. However, Brav, Geczy & Gompers (2000) explore this anomaly for the period between 1975 and 1992, finding that the underperformance mostly persists with small firms that exhibit low book-to-market values. They therefore conclude that the issuance effect, as presented by Loughran & Ritter (1995), might be overstated for the universe of publicly-traded companies as a whole.

Loughran & Vijh (1997) assess the influence of acquisitions (and their elected payment type) on stock returns. By following 947 acquisitions over a 19-year period starting 1970 they find that, over the five-year post-merger period, firms using stock swaps as a way to finance acquisitions experience a underperformance of -25%, while firms implementing all-cash takeovers exhibit positive excess returns of 61.7%. They also find that target shareholders holding acquirer stock over the same period do not realize significant positive excess returns.

2.3.2.2.2 Corporate Governance

Gompers, Ishii & Metrick (2003) assess the influence of corporate governance, specifically shareholder rights, on stock performance. In order to do so, they construct a governance index based on the incidence of 24 corporate governance rules, which they use as proxy for shareholder rights among a universe of ~1500 companies during the period of the 1990s. By building zero-cost portfolios that are long the lowest scoring index firms that signal the strongest shareholder rights and simultaneously shorting the decile of the highest scoring index firms, they obtain average excess returns of ~8.5% per annum. Furthermore, they observe that companies with more pronounced shareholder rights opt for fewer corporate acquisitions and exhibit higher entity values, higher profits, above average sales growth and lower discretionary capital expenditures. However, when considering different possible explanations for these observations, the authors find that the data does not allow for strong conclusions about causality. Thus, only based on their findings, changing strength of corporate governance in individually observed firms should likely not be used as an indicator for changes in future expected performance.

Chan, Chan, Jegadeesh & Lakonishok (2001) discuss the impact of earnings quality on stock returns. They address the notion that the markets focus on bottom-line earnings is so dominant that other operating performance indicators are increasingly neglected. Therefore, the impact of managerial discretion on accounting decisions is potentially ignored and gives opportunity to manipulate earnings growth. The authors show that accruals, the difference between actual cash flows and reported accounting earnings, exhibit a negative association with future stock returns. They identify working capital accruals as the positions with the most significant predictable power.

Interestingly, changes in all three working capital positions are negatively correlated with future stock returns. The authors discuss several possible explanations for this finding: A) High accrual levels, whether positive or negative, can complement the perception of earnings manipulation by management. B) A change in accruals relating to accounts payable can help signal future business prospects. An accounts payable increase could imply a firm's weakened financial position, prompting the decision to delay payments to suppliers. C) Accruals might serve as a significant indicator of changes in a company's operating prospects, without any explicit actions undertaken by management to deliberately manipulate accounting earnings. D) Accruals could predict future stock returns in scenarios in which market participants interpret accruals as a reflection of past growth and form expectations towards future stock performance on this basis. The authors believe that all of the mentioned implications could potentially be true for some individual firms. Thus, they further underline the importance of analyzing different accruals individually, as the use of a simple catch-all accrual adjustment potentially undermines the predictive power of the measure.

Core, Holthausen & Larcker (1999) examine the influence of a company's ownership structure and board composition on CEO compensation. They find evidence for the notion that executive compensation is negatively correlated to the efficiency of corporate governance, hinting at the existence of agency problems. The authors find that governance efficiency is lower in scenarios where the CEO is also the chair of the board of directors, the number of board members is large, the number of outside directors is large and the outside directors are appointed by the CEO. Furthermore, they identify a significantly negative correlation between executive compensation arising through weak governance and a company's operating and stock return performance.

2.4 Connections with the paper at hand

Our paper sets out to examine the ability of different components of financial statement analysis, both individually and in combination, to provide investors with incremental information that enables excess returns unexplained by current empirical asset pricing methods. Importantly, we do not aim to develop or enhance a systematic risk factor on our own. Instead, we will use our findings to build an investment strategy that captures excess returns. However, our assessment and subsequent use of financial ratios could potentially provide incentives for future research to develop new or further specify existing systematic risk factors in a way that explains observed excess returns as risk premia aligned to these specifications.

Through the establishment and control of our investment strategy, we aim to show that fundamental analysis can to date still drive the identification of positive excess returns, both for individual ratios as well as in combination. To do so, we prolong the sample period to include the most recent available data, covering all U.S. common stocks from July 1966 to December 2016 in its entirety, with the exception of financial firms.

For value investors and fundamental analysts, our findings can provide evidence on the suitability of specific ratios and, consequently, how the perceived information content should be ranked throughout the process of fundamental analysis.

Furthermore, we do not intend to make explicitly claims to confirm or reject the Efficient Market Hypothesis, but we will implicitly show that current popular empirical asset pricing models fail to explain return cross-sections in their entirety.

Finally, we also do not intend to explicitly provide evidence supporting hypotheses from the area of behavioral finance. However, the observation that fundamental analysis can enable investors to achieve positive excess returns could be driven by behavioral implications on investment decision making, especially if empirical asset pricing models continue to proof unable to explain them through loadings of refined risk-factors. Potential behavioral connections could be a reduction in perceived uncertainty through the process of analysis and the use of fundamental analysis as a basis for decision making algorithms reducing human misjudgment, as well as a balancing tool to counter overconfidence and over-/ under-reaction to new information. Whether or not fundamental analysis convincingly achieves these feats in practice remains subject to further research.

3. Empirical Analysis

In this part of our thesis, we will investigate on the ability of stock picking based on different fundamental metrics. We will try to filter out the ratios which add value in successfully laying out the quantitative part within our value investing model. To understand these characteristics, we first conduct cross-sectional regressions of a selection of indicator measures, followed by a persistence analysis and univariate sorts on the different metrics. The resulting overviews should give us a good indication on which measures to include in our value investing strategy. Subsequently, we will establish this strategy by combining different measures in accordance with the procedure of Asness, Frazzini & Pedersen (2014). Finally, different controls are applied to examine the robustness of our results in altering empirical preconditions.

3.1 Data Sources, Methodology and Descriptive Statistics

This section describes the data sources used in this thesis, defines the general methodology applied in our analysis and discusses summary statistics of the investigated measures that will ultimately lead to our proposed value investing strategy.

3.1.1 Data Sources

The sourcing of the data used in our empirical analysis can be divided in three different groups, which will be further detailed in this section.

First, the CRSP US Stock Database provides our monthly market data, which among others include holding period return, delisting return, price, shares outstanding and trading volume. We access CRSP through WRDS (Wharton Research Data Services). Our sample comprises 31,054 U.S. stocks covering a period from 01/1963 to 12/2016. The starting date was chosen to be one year after the NYSE MKT (previously AMEX) inclusion within the database as we need an initial lag of one fiscal year of accounting data for the sorting. The ending date refers to the last full year available.

Second, the CRSP/Compustat Merged Database allows us to access Compustat's Xpressfeed fundamental data (provided by S&P Capital IQ), which is already linked to CRSP over a permanent security identifier. Again, the service is accessed via WRDS. As reasoned earlier, we chose a sample range from 01/1962 to 12/2016 containing U.S. stock accounting data with several financial statement items.

Third, for the data required in the analysis of factor loadings, we mainly resort to Kenneth R. French's data library, which provides a market factor[1], the size factor SMB ("Small Minus Big" on size), the value factor HML ("High Minus Low" on book-to-market), the profitability factor RMW ("Robust Minus Weak" on operating profitability) and the investment factor CMA ("Conservative Minus Aggressive" on investment).

All data sources are commonly used by a wide range of renowned researchers, some of who are also frequently referenced in this thesis, e.g. Eugene Fama, Kenneth French, Clifford S. Asness, Andrea Frazzini, Lasse H. Pedersen, Robert Novy-Marx (Fama and French (1993), Asness et. al. (2014), Novy-Marx (2013)). We thus consider our data sources as reliant and qualified.

3.1.2 Methodology

The returns applied in this thesis include dividends, are denoted in USD and are measured as excess returns above the one-month U.S. Treasury bill rate. To mitigate the distortion of our results by survivorship bias, the stock specific time series of returns is expanded by the delisting return in the month after it last traded. Even though the actual effect of the delisting returns is vanishingly small, we consider the inclusion important as we are also examining the characteristics of valuation ratios, where a low price might indicate higher risk of financial distress. From the market data, we further define market capitalization as stock price times shares outstanding.

To empirically analyze fundamental ratios, we must make sure that the accounting data is available at the date of portfolio formation. Consequently, we apply the conservative approach of aligning a firm's fundamentals for a given fiscal year at June in the following calendar year. The return series thus begins in July, after the portfolio formation is realized. When picking the fundamental ratios for our empirical analysis, we tried to choose the most holistic and commonly used measures among value investors. To cover the entire scope of the quantitative side, we separated the measures in different groups, which will be further defined in the following. Most generally, we will differentiate between a 'performance' and 'inexpensiveness' group for which we calculate several metrics from the financial statement items. While the performance group can

[1] Excess return on the market, value-weight return of all CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX or NASDAQ (shrcd 10 or 11)

be subdivided in what we name profitability, operating activity, financial stability and growth measures, the inexpensiveness group solely consists of valuation ratios. Often, shareholder friendliness is mentioned along these lines. Yet, we excluded it from our analysis as payout ratios by themselves cannot be seen as holistic measures considering the variety of interpretation possibilities in regards to investment possibilities. We decided to follow well established research on the general construction approach of our metrics as there is no consensus on the actual calculation of fundamental ratios among value investing practitioners. The calculation of performance measures follows Novy-Marx (2013) and Asness et. al. (2014). For profitability, we calculated gross profits-to-assets (gross profits over total assets), return on capital employed (operating income over capital employed), return on equity (income before extraordinary items over book equity), free cash flow over capital employed and EBITDA margin (EBITDA over total revenue). For operating activity, we use asset turnover (sales over total assets) and working capital turnover (sales over working capital) as holistic measures indicating the overall efficiency of a company. For financial stability, we consider the equity-to-debt ratio (book equity over debt) and the equity-to-assets ratio (equity over assets) as solvency measures and the current ratio (current assets over current liabilities) and cash-to-sales ratio as liquidity measures. Finally, growth is measured through the three-year growth in gross profits-to-assets (gross profits-to-assets at t divided by gross profits-to-assets at t minus three years) and the three-year growth in free cash flow-to-assets (free cash flow-to-assets at t divided by free cash flow-to-assets at t minus three years). The calculation of inexpensiveness measures is based on the recognized approach of Fama-French (1993). To avoid an implicit short momentum position, when constructing strategies based on valuation ratios, sorting variables in June are scaled by market equity from the end of December of the preceding year to match the time horizon of the fundamentals. We consider three different valuation ratios for our inexpensiveness group: The book-to-market ratio (book equity at t over market equity at t minus 6 months), the earnings-to-price ratio (income before extraordinary items at t over market equity at t minus 6 months) and the free cash flow-to-price ratio (free cash flow at t over market equity at t minus 6 months). For the two latter ratios, price refers to market equity, which is in accordance with the standard convention in empirical research but might deviate from the practitioner's perspective where the market price is divided by the fundamental variable on a weighted average number of shares basis. While this might produce different results in the case of a seasoned equity offering, it still captures the characteristics of the valuation variable nonetheless.

A more detailed description on the construction of both performance and inexpensiveness metrics can be found in Appendix I.

Following Asness et. al (2014), we use z-scores for the persistence analysis and multivariate sorting strategies. On the one hand, z-scores allow for comparability among our wide range of measures that show very different magnitudes and cross-sectional variation. On the other hand, they enable the construction of multivariate scores as each z-score can be simply combined by weighting schemes into a composite final z-score. The z-scores $z(x)$ can be defined as standardized cross-sectional ranks of each indicator measure x, where $z(x) = (r - \mu_r)/\sigma_r$, with r as the vector of ranks $r_i = rank(x_i)$, μ_r as the cross-sectional mean of r and σ_r as the cross-sectional standard deviation of r.

Turning to the more general methodology in the construction of our quantile portfolios, we want to discuss three conditions. To begin with, our quantile portfolios are constructed with NYSE breakpoints. Each portfolio thus contains the same number of stocks listed on the NYSE. This is common practice for US stock market research (e.g. Fama & French, 2015) in order to circumvent an accumulation of small stocks from the AMEX and NASDAQ exchanges within one of the quantile portfolios. This becomes particularly important when portfolios are equally weighted as small cap stocks already have a higher effect on the results due to their large number compared to large cap stocks. Yet, having a value investing perspective, which is based on idiosyncratic stock picking and does not distinguish between large and small cap stocks, equally-weighted portfolios are the only viable option. Consequently, we perform robustness tests of our proposed strategy dividing our sample in small, mid and large cap stocks to account for the possibility of skewed results due to the tendency of higher volatility in small cap stocks. Lastly, we use decile portfolios in contrast to quintile portfolios as it not only allows for a higher dispersion between the extreme high and low quantile portfolios but also reduces the theoretical implementation costs (Perold, 1988) due to the lower number of stocks in each quantile. This becomes important when assessing the economic vs. statistical significance of our results (Malkiel, 2003) as we set a high focus on the practical applicability of our strategy.

Throughout this thesis, we decided to exclude some firms from the dataset based on previous research and to be in accordance with value investing theory. First, we follow the standard approach used in most investigated research papers (e.g. Fama and French, 2015) to only include common stock (CRSP shrcd equal to 10 or 11). ADRs, REITs and other non-common stocks which are subject to differing market conditions are thus excluded from our dataset. Second, we follow Novy-

Marx (2013) and exclude firms operating in the financial sector (one-digit SIC code of 6) whose assets exhibit very different characteristics (i.e. are considerably larger due to often high leverage) than non-financial firms. As most of our indicator metrics have been scales by some form of assets, the exclusion of financial firms further reduces the likelihood of a distortion of our empirical results. Third, we only consider positive indicator metrics as we want to investigate on firms being in a healthy and ordinary state of business. This is in accordance with both empirical research (Fama & French, 1993) and from a value investing practitioner's perspective, who would likely neglect firms with negative earnings or other discrediting indicators. All three exclusions are applied to all results displayed in this thesis.

3.1.3 Descriptive Statistics

Table I shows summary statistics of the indicator measures for the full sample (1966-2016), subsample I (1966-1992) and subsample II (1993-2016). For each metric and sample, we report four different variables. First, the average number of stocks refers to the time series average of the number of firms with a valid observation as of June each year, the month of portfolio formation in subsequent tests. Second, the mean refers to the time series average of the cross-sectional mean of the respective metric in June each year. Third, the standard deviation refers to the time series average of the cross-sectional standard deviation of the respective metric in June each year. Fourth, the coefficient of variance refers to the time series average of the cross-sectional coefficient of variance of the respective metric in June each year.

Firstly, for every chosen sorting metric, with the exception of return on equity and earnings-to-price, we see an increase in average numbers of stocks in the second subsample. This observation is likely unsurprising, as one would expect an increase in publicly traded companies over time through the opening of financial markets to both, broader sets of investors and thus, as a result of increased demand, to a broader number of companies representing new investment opportunities. The lowest average number of observations obtained is for the Free Cash Flow-to-Price ratio in subsample one, with 1743 average observations per annum in subsample one. Respectively, the highest number of observations can be obtained for the asset turnover ratio, with average 3377 observations per annum in subsample one and average 4097 per annum observations in subsample two.

The lowest observed cross-sectional means relate to the earnings-to-price and the free cash flow-to-assets ratios, for all samples. Both observations report a coefficient of variation of around

1.40% for the full sample, with the coefficient of variance for free cash flow-to-assets remaining stable over the subsamples but deteriorating for the earnings-to-price ratio from 0.81% in subsample one to 2.37% in subsample two. The same observation can be made for the book-to-market ratio and asset turnover, both of which experience a decrease in their cross-sectional means over the subsamples, with a simultaneous increase in standard deviation exhibited by the book-to-market ratio (standard deviation for asset turnover remains largely stable). When putting the cross-sectional mean in relation to its standard deviation, the gross profit-to-asset and the equity-to-asset seem to show the lowest coefficient of variation and thus appear to exhibit the strongest predictive power, with the relation remaining largely stable over the subsamples. Looking only at the full sample, the EBITDA margin seems to be of equal predictive power, however an investigation of the subsamples shows that this is largely driven by subsample one, while in subsample two the coefficient of variation deteriorated to 1.45%, up from 0.51% in subsample one. Asset turnover strikes as the metric displaying the least variation, reporting a cross-sectional mean of 1.25% with the third lowest coefficient of variance at 0.81% for the full sample. While the observations deteriorated marginally from subsample one to subsample two, we still report a mean of 1.09% and a coefficient of variance of 0.90% for the more recent subsample two.

3.2 Fama-MacBeth Regressions

This section outlines cross-sectional regressions of monthly returns on performance measures to get an initial sense as to which measure works as a good indicator and thus might ultimately provide value for a value investor. We perform both univariate and multivariate monthly Fama-MacBeth (1973) regressions to select measures individually and to test them jointly to identify superior measures. We lag the measures by one month to allow for predictability conclusions and winsorize ('cut') the measures at the 1% and 99% levels to avoid extreme outliers which disproportionally skew linear regression results. Yet, fundamentals are only available once a year in our dataset. The annual measures previously registered in June each year are thus lagged to July and subsequently extended until June in the following year to have consecutive time series of observations, which can be used in the Fama-MacBeth regressions. Assuming n independent variables, the cross-sectional regressions will take the form $r_{tj} = \alpha_t + \beta_t' x_{tj} + \varepsilon_{tj}$ with r_{tj} as the return for stock j in month t, β_t $(n \times 1)$ as the vector of slope coefficients and x_{tj} $(n \times 1)$ as the vector of independent variables for stock j in month t. The regression is performed every month from July 1966 to

December 2016, amounting to 606 months. We consequently report the slope coefficients in Table II as time-series averages of the resulting slope coefficient vectors. Three different panels are displayed. We show cross-sectional regressions on profitability measures in Panel A individually and jointly. The same applies for supplementary measures in Panel B. Picking the metrics with the most predictive power judging from Panel A and B, we pursue joint tests in Panel C and include controls following Novy-Marx (2013) for book-to-market ($\log(\mathrm{B/M})$), size ($\log(\text{market cap})$) and past cumulative returns measured at horizons of one month ($r_{1,0}$) and twelve to two months ($r_{12,2}$). The logarithms are used to counteract the high variation and skew in book-to-market ratio and market capitalization.

Panel A shows that the gross profits-to-assets ratio has the strongest predictive power over the cross-section of returns among our presented universe of profitability metrics, both when tested individually as well as multivariate. However, unsurprisingly the predictive power is somewhat smaller in our multivariate test, given the introduction of other indicators. Still it remains high on an absolute basis and it appears that the gross profits-to-assets ratio subsumes the other profitability metrics. Return on equity and EBITDA margin also exhibit some predictive power when tested on the 5% and 10% confidence level, individually. Interestingly, while return on equity maintains its predictive power with 5% confidence in the multivariate test, EBITDA margin loses significance in predictive ability and instead is replaced by return on capital employed which offers somewhat statistically significant prediction on a 10% confidence level even though it did not account as statistically significant predictor in individual testing.

For the chosen supplementary metrics in consideration, as displayed in Panel B, asset turnover and gross profit growth exhibit the most significant predictive ability on individual metric level, satisfying 1% levels of confidence. Additionally, the equity-to-assets ratio seems to have some predictive ability, satisfying a 5% confidence level. However, assessing our multivariate regression, only asset turnover remains a significant predictor with 1% confidence level. Both equity-to-assets ratio and asset turnover appear to lose their predictive ability in a multivariate regression, not satisfying 10% confidence levels. Instead, the cash-to-sales ratio seems to gain in predictive ability, satisfying a 10% confidence level in the multivariate regression. Lastly, working capital turnover, equity-to-debt and current ratio display no predictive power, neither in the univariate, nor in the multivariate regressions.

Panel C shows that gross profits-to-assets maintains its predictive ability after being controlled for variables discussed in the beginning of this section. This observation is in line with Novy-Marx

(2013) finding that high profitably firms generate higher average returns than less profitable ones. Asset turnover, equity-to-assets and gross profit growth ratios, while still being statistically significant, exhibit somewhat less predictive power than the gross profits-to-assets ratio. When combining gross profits-to-assets and asset turnover ratio, the predictive ability of the gross profits-to-assets ratio is enhanced, however the predictive ability of asset turnover becomes statistically insignificant. When using equity-to-assets and gross profit growth ratios in combination with gross profits-to-assets, the predictive ability of each metric diminishes somewhat but remains high, with gross profits-to-assets ratio remaining statistically significant at 1% confidence levels and equity-to-asset and gross profit growth ratio being statistically significant only at 5% confidence levels. When using all four metrics, gross profits-to-assets, asset turnover, equity-to-assets and gross profits growth, the gross profits-to-assets ratio remains statistically significant, with gross profits-to-assets exhibiting a slightly stronger predictive ability. Gross profit growth remains an incrementally significant predictor on the 5% confidence level, while asset turnover and equity-to-assets ratios appear statistically insignificant. Specifications 2 to 8 thus show that gross profits-to-assets subsumes the other profitability variables.

In accordance to Novy-Marx (2013) we find that gross profitability is a powerful predictor in the cross-section of returns. While gross profit growth also exhibits some power, asset turnover and equity-to-asset ratios arguably offer little added information regarding future earnings, when used in combination. However, they exhibit some predictor power when observed individually. As discussed in our methodology description at the beginning of this paragraph and again in accordance to Novy-Marx (2013) we must consider that observed regressions are somewhat skewed, as they weigh each observation equally and as such put increased focus on small cap stocks. These stocks, while accounting for the majority of firms in our sample, make up only a fraction of the market size measured by capitalization. Furthermore, as Novy-Marx (2013) notes, Fama Macbeth regressions are sensitive to outliers as well and consequently might "impose a potentially misspecified parametric relation between the variables" (Novy-Marx, 2013), that potentially undermines the economic significance of observed results. However, we believe our efforts to winzorize performance measures and apply logarithmic controls should counter this skewing.

3.3 Persistence of Performance Measures

This section examines the persistence of performance measures, i.e. shows an analysis whether stocks with high performance measures today also exhibit these characteristics in the future (Asness et. al., 2014). We included this section for two reasons. First, we want to specifically understand which performance measures are good indicators for a higher return in the future. If the analyzed metrics would not be persistent in time, a link between return and metric is expected to be less significant. Second, having a value investing perspective, which tends to yield a longer investment horizon than other stock picking strategies, puts an emphasis on the sustainability of sorting indicators. Strongly persistent performance measures should thus be more valuable than non-persistent ones. We only analyze performance measures as persistence is no criterion for inexpensiveness (i.e. valuation) metrics.

Table III reports time-series averages of equally-weighted cross-sectional average z-scores of performance measures for decile portfolios at the date of portfolio formation (t) and their respective scores five years after ($t + 60$). In each June from 1966 to 2016 and for every performance measure, stocks are sorted in ascending order based on their z-scores and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. We then calculate the equally-weighted cross-sectional average of the stock individual z-scores at t and at $t + 60$, keeping the stocks in the same portfolio for the respective year. The resulting two time-series (for t and $t + 60$) are averaged and presented in Table III. As the z-scores at t must increase monotonically from the 'low' decile portfolio to the 'high' decile portfolio due to the method of construction, the z-scores at $t + 60$ only increase monotonically when stocks continue showing the characteristics being examined. Table A1 in the Appendix shows a more detailed breakdown of each measure up to ten years.

Table III displays a detailed view of the persistence of performance measures with Panel A relating to chosen profitability metrics and Panel B relating to supplementary metrics. By construction, corresponding to Asness et. al. (2014), the observed quality scores exhibit a monotonic variation across portfolios at time t of portfolio formation. To assess the persistence of chosen metrics, we must focus on the quality score developments observed for the time $t + 60$.

We find gross profits (GP)-to-assets, GP margin and EBITDA margin to exhibit the strongest persistence over the time frame in consideration. The cash flow measures Free Cash Flow (FCF)-to-assets and FCF-to-capital employed (CE) exhibit the lowest persistence. However, we find persistence in every investigated profitability metrics. As such, we can claim that profitability is a persistent firm characteristic, on average high profitability firms are likely to remain high profitability firms over the next five years. This observation is in line with the one of Asness et. al. (2014), who find persistency of profitability as quality characteristic to maintain even over a 10 year (120 month) period. The fact that the GP-to-assets ratio, as well as the considered margins, exhibit higher persistence than return on equity or chosen FCF metrics is likely inherent in the nature of the metrics themselves, more specifically in the stability or variability of the underlying fundamental inputs. For example, net income today as measured as a fraction of a company's equity, will through retained earnings directly translate in an increase of a company's equity tomorrow. The company could use these funds for a variety of initiatives, including positive NPV investments, but the available investment IRRs might be lower than the ones currently obtained (when faced with scarcity of capital, companies likely perform the highest IRR investment first, thus consequently with more capital lower IRR investments become more prominent alternatives). Interestingly, for the chosen FCF metrics we do not find a strict monotonous variety in $t + 60$ persistence measures, as the P1 portfolio for both performs slightly, albeit marginally, better than the P2 portfolio. Due to the volatile nature of FCF generation, especially in firms with low profitability and potentially close to distress, this observation does not necessarily come as a surprise.

For the chosen supplementary metrics, as displayed in Panel B, the picture is less clear. Asset turnover, working capital turnover, equity-to-debt, equity-to-assets, current ratio and cash-to-sales ratio exhibit strong persistence over time, even more so than return on equity and return on capital employed did, as shown in Panel A. However, gross profit and free cash flow growth both are not persistent, instead gross profit growth actually develops negatively. From these observations, we find that companies who effectively manage their operating activities and their capital structure are on average likely to continue doing so in the future (again considering our 60 months' time frame). However, companies that exhibit strong gross profit and free cash flow growth today are at least unlikely to do so in the future. Fundamentally, that should again not come as a huge surprise. Both measures are relative growth measures, thus with high gross profits and free cash flows today it will become increasingly harder to consistently grow at high rates in the future. This is especially true for large capitalization stocks that reached a mature state as a company. For these companies, highly positive NPV investment opportunities are increasingly scarce and hard to come by. Often, they face markets whose demands are fully captured, and their success brought new entrants and thus increased competition, undermining their cost cutting ability. Therefore, we assess the benefit to the inclusion of gross profit and free cash flow growth measures for value investors as strongly dependent on the investment horizon and/ or portfolio rebalancing intervals. The shorter those are, the higher is the information content offered by the inclusion of these metrics.

Focusing on operational activity, the asset turnover ratio is more persistent than the working capital turnover ratio. Both ratios have sales in the numerator with total assets as denominator for asset turnover and working capital as denominator for working capital turnover. Fundamentally it seems easy to see that measuring working capital is much more prone to volatility as the total asset base. Small changes in terms of payments, both by the company itself and its suppliers can have major distorting impact on the metrics. Furthermore, working capital in itself is included in total assets. Thus, given its persistence, comparatively lower proneness to direct manipulation and overall information content, asset turnover appears to be the more valuable metric for value investors.

In regards to solvency, equity-to-debt and equity-to-asset ratios display almost identical levels of persistence, with equity-to-debt arguably fairing incrementally better. As assets are largely balanced by equity and debt on the liability side, that does not strike us as surprising. While equity-to-debt might provide somewhat clearer information on a company's debt burden, no single metric strikes as the more attractive metric to be chosen, if an assessment is only based on these observations.

When assessing a company's liquidity, the current ratio exhibit stronger persistence than the cash-to-sales ratio. On the basis of their underlying fundamentals, the information content regarding a company's ability to fulfil its short-term obligations is also arguably higher for the current ratio, than it is for the cash-to-sales ratio. Thus, if one must choose, the current ratio should likely prevail.

3.4 Univariate Strategies

This section will show performance figures for univariate strategies based on our indicator measures. Together with our previous findings, we should be able to filter out the measures which will add most value in the multivariate value investing strategy that we will propose.

Table IV reports monthly excess returns ($E[r^e]$), monthly abnormal returns (α), annualized Sharpe ratios and annualized Information ratios for long-short extreme decile portfolios (H-L) of strategies formed by sorting on indicator measures. In each June and for each indicator measure, stocks are sorted in ascending order based on their z-scores and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. We then calculate equally weighted returns for each decile portfolio for every of the subsequent 12 months, starting in July of the same year and ending in June of the following year. With a sample running from July 1966 to December 2016, we have 606 months for which we compute the monthly time-series average of excess returns that will be reported for each measure in Table IV. Furthermore, we show monthly abnormal returns relative to the CAPM, Fama-French three-factor model and Fama-French five-factor model. In addition to it, annualized Sharpe and Information ratios are displayed.

Panel A displays statistically significant excess returns of 0.79% per month for high minus low profitability stocks sorted based on gross profits-to-assets. These high excess returns remain largely unexplained by both, the CAPM and the Fama & French three- (FF3) and five-factor (FF5) models, respectively. As such, we report a CAPM alpha of 0.76%, a FF3 alpha of 0.79% and a FF5 alpha of 0.51%, all with strong statistical significance. While the CAPM and FF3 alpha in themselves are unsurprising, as one of the FF5 added factors specifically focuses on a perceived anomaly of profitability mispricing, it is interesting to see that also the FF5 model with its factor specification for a company's profitability fails to explain our returns. A potential reason for this observation could be, that the FF5 profitability factor is wrongly specified and the gross profits-to-assets ratio incorporates additional information.

While we find statistically significant negative excess return and CAPM alpha for a strategy sorted on return on equity, the FF3 and FF5 models appear to do a good job to explain those with systemic risk factor loadings. For strategies focused on return on capital employed and EBITDA margin, we do not find statistically significant excess returns, nor abnormal returns regarding to the different systematic risk factor models in consideration. This comes with the exception of the observation of return on capital employed, as this portfolio shows minor abnormal returns of 0.15% per month on a 10% confidence level in regard to the FF3 model. These minor abnormal returns appear to be largely explained by the FF5 model, however.

Strikingly, while we do not report statistically significant excess returns and abnormal returns regarding the CAPM for gross profit margin and the free cash flow-to-assets ratio, when testing them against the FF3 and FF5 model we observe statistically significant abnormal returns. For the FF5 model, these average 0.49% per month for the strategy sorting on gross profit margin and 0.23% per month for the strategy sorting on free cash flow-to-assets.

Another interesting observation is, that we report negative excess returns for portfolio strategies sorting on return on capital employed, return on equity, EBITDA margin and free cash flow-to-capital employed, however only the excess return observed for return on equity is statistically significant and, as explained earlier, seemingly explained by the FF3 and FF5 models.

Panel B displays the performance of portfolio strategies sorting in regard to our chosen supplementary ratios. We report large and statistically significant excess returns for asset turnover (0.63% per month), equity-to-debt (0.28% per month), equity-to-assets (0.28% per month), current ratio (0.44% per month) and gross profit growth (0.44% per month).

For asset turnover, we also report large and statistically significant abnormal returns in relation to the CAPM and FF3 model. However, the FF5 model seems to explain those in their entirety. Strikingly, while we do not report statistically significant excess and abnormal returns in relation to CAPM and FF3 for working capital turnover, we report large negative and statistically significant abnormal returns in relation to the FF5 model.

For equity-to-debt, equity-to-assets, current ratio and gross profit growth, we report consistent large and statistically significant abnormal returns in relation to all of the three systematic risk factor models in consideration. A portfolio strategy sorting on equity-to-debt offers 0.70% per months of abnormal returns over the FF5 model, 3 basis points more than a strategy sorting on equity-to-assets, while having a somewhat stronger statistical significance. A strategy sorting on current ratios offers 0.62% monthly abnormal return over the FF5 model, a strategy sorting on gross profit growth still 0.41% abnormal return per month. Interestingly, a portfolio strategy sorting on cash-to-sales only reports statistically significant abnormal returns when compared to the FF5 model, the same observation that we made for the strategy centering on working capital turnover.

Interestingly, the sorting based on the supplementary ratios that exhibit the strongest persistence among their sub class pairs (asset turnover for operational activity, equity-to-debt for solvency and current ratio for liquidity) also exhibit the highest and most statistical significant excess and abnormal returns, with the exception of asset turnover under the FF5 model, as discussed before. It appears reasonable that the most persistent characteristics should also be priced accordingly.

Lastly, Panel C displays the excess and abnormal returns of portfolio strategies sorting on the basis of popular valuation metrics, namely book-to-market, earnings-to-price and free cash flow-to-price. It is striking that strategies focused on all three of these metrics individually demand high and statistically significant excess and abnormal returns over the CAPM, FF3 and FF5 models, especially as an aim of the FF3 and FF5 models was to explain return anomalies based on company size and value characteristics. We report FF5 abnormal returns of 0.56% per month for book-to-market, 0.31% monthly for earnings-to-price and 0.33% per month for free cash flow-to-price, respectively. While those correspond to roughly 50% of the observed excess return per metric, it is still puzzling that only half of them can be explained by FF5.

We find that gross profit-to-assets displays the largest Sharpe Ratio (0.98) and second largest Information Ratio (0.75) among the investigated profitability strategies. For the supplementary strategies, gross profit growth shows the largest Sharpe Ratio (0.81), while equity-to-debt displays the largest Information Ratio (1.16). For the investigated valuation strategies, book-to-market displays both, the largest Sharpe Ratio (0.92) and the largest Information Ratio (0.79).

Following these observations, we can make a well-founded judgement on which metrics we intend to include in our following multivariate portfolio strategy.

3.5 Multivariate Strategy

With the information from the previous sections, we propose a strategy which combines z-scores that each cover one of the categories defined at the beginning of our empirical analysis. For profitability, we use the gross profits-to-assets ratio, as it sustains both previous research from renowned researchers (Novy-Marx, 2013) and dominates our profitability group in each of the tests we pursued. Due to its superiority above asset turnover, we also concluded that the gross profit-to-assets ratio indeed covers efficiency so that we exclude the efficiency-specific category from our analysis. For solvency, sorts and cross-sectional regressions on the equity-to-assets ratio showed more significant results than the debt-to-equity ratio. Consequently, we chose the solvency ratio as our first financial stability measure. Continuing with liquidity, the current ratio did not survive the cross-sectional regressions but showed significant excess returns at the univariate sorts. Due to the previously discussed flaws of Fama-MacBeth regressions for our purpose, we decided to put a higher weight on the univariate sorts and therefore include the current ratio in our strategy. The latter thus constitutes our second financial stability measure. Finally, even though growth numbers are not persistent at the five-year horizons, we showed in the appendix that they are persistent for one year. Having the impressive results on both cross-sectional regressions and univariate sorts, it only makes sense to also include the growth in gross profits-to-assets. Lastly, we use the book-to-market ratio as our inexpensiveness metric as it shows the highest excess returns on the univariate sorts and has been extensively verified by notable researchers (e.g. Fama and French, 1993). We thus have gross profits-to-assets, equity-to-assets, current ratio, gross profit growth and book-to-market ratio to be included in our strategy. With the advantage of having z-scores, we can now combine each measure into a single z-score. Asness et. al. (2014) equally weight each measure within their category and afterwards across categories but they also have a more generic approach when it comes to choosing the indicator measures analyzed since every measure is included despite their individual properties. Consequently, we also weight our five indicator measures according to their predictive ability with the weighting scheme $z_{multivariate} = 0.4 \times z_{b/m} + 0.3 \times z_{gpa} + 0.075 \times z_{eta} + 0.075 \times z_{cr} + 0.15 \times z_{gpgr}$, which should resemble a typical value investing strategy that places high importance to valuation and profitability, while other ratios act more like supplementary decision criteria. Yet, the weighting scheme can be perceived as subjective and therefore we will test alternative scenarios in our robustness section.

With the final z-score $z_{multivariate}$ we can construct our strategy as follows. In each June, stocks are sorted in ascending order based on the final z-score $z_{multivariate}$ and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. We then calculate equally weighted returns for each decile portfolio for the subsequent 12 months, starting in July of the same year and ending in June of the following year. With a sample running from July 1966 to December 2016, we have 606 months for which we compute the monthly time-series average of excess returns that will be reported for each measure in Table V. Furthermore, we show monthly abnormal returns relative to the CAPM, Fama-French three-factor model and Fama-French five-factor model. In addition to it, annualized Sharpe and Information ratios are displayed.

First thing we note from our observations in Table V is that both excess returns and abnormal returns relating to the three chosen factor models display a monotonous development, with stock portfolios consisting of higher value characteristic companies, as defined by our $z_{multivariate}$ z-scores, demand higher returns than portfolios of lower z-score companies. This observation is somewhat surprising from an efficient market perspective, as higher value characteristic firms should demand higher prices and therefore offer lower excess and abnormal returns than lower value firms. It does, however, support our hypothesis that high value characteristics are largely underpriced by the market and an investment strategy focused on identifying value from publicly available information will yield both, excess and abnormal returns to the savvy investor.

Apart from the lowest z-score portfolio, we report large and statistically significant excess returns for all our constructed decile portfolios. The observed monthly excess returns range from

1.41% for the highest z-score P10 portfolio to 0.52% for the second lowest value portfolio P2. While the reported excess return for the lowest z-score portfolio P1 is comparatively small at 0.15% per month and not statistically significant, we find that our zero-cost H-L portfolio formed by going long P10 and short P1 yields a 1.26% positive excess return per month with almost double the statistical significance of the highest significance individual portfolio. Overall we find that the statistical significance of observed excess returns is generally higher for the higher z-score portfolios.

Further, we find both Sharpe and Information Ratios to monotonically increase from P1 (low) to P10 (high). The zero-cost H-L portfolio exhibits a Sharpe Ratio 1.40 of and an Information Ratio of 1.33, which are higher than all sorting strategies based on individual indicator metrics in Table IV.

The observed abnormal returns in relation to the chosen empirical asset pricing models paint a similar picture. Interestingly, when looking at the CAPM, we report large and statistically significant excess returns for the 5 highest z-score portfolios as well as for the lowest z-score portfolio P1, as well as slightly less but still statistically significant positive abnormal returns for the average z-score portfolio P5. The lower z-score portfolios P2 to P4 do not exhibit large abnormal returns and also do not display statistical significance. The lowest z-score portfolio P1 shows large negative abnormal returns of -0.47% per month, hinting that the lowest z-score companies are actually significantly overpriced even compared to their CAPM factor loading. On the other hand, we find portfolios P6 to P10 significantly underpriced, reporting abnormal returns as high as 0.88% per month for P10.

Looking at the abnormal returns of our portfolios in relation to the FF3 and FF5 models, we again find them to be large and statistically significant for the lowest portfolio P1 and the higher value portfolios P7 to P10. For P1 we observe negative abnormal returns at -0.55% for the FF3 and -0.43% for the FF5 model. For the high value portfolios P7 to P10 we report considerable positive abnormal returns ranging between 0.21% and 0.55% per month for the FF3 and between 0.19% and 0.52% per month for the FF5 model. The low value portfolios P2 to P4 display some negative abnormal returns in the range between -0.11% to -0.16% per month for the FF3 and in the range between -0.13% to -0.15% per month for the FF5 model. These abnormal returns also exhibit some statistical significance on the 5% and the 10% confidence levels. The medium value portfolio P5 again does not display considerable abnormal returns and also exhibits no statistical significance. The other medium value portfolio P6 lastly displays minor abnormal returns, with statistical significance on the 10% confidence level for the FF3 model and no statistical significance regarding the FF5 model. Interestingly, while our z-score based investment strategy puts a lot of weight on a firm's profitability score, the FF5 model performs only marginally better than the FF3 model in terms of explaining our observed abnormal returns. This again raises the question whether the Fama & French (2015) five-factor model uses a profitability factor with the right specifications.

Focusing on our constructed zero-cost portfolio H-L, the earlier discussed large and statistically significant excess returns are supported by also large and statistically significant abnormal returns over the systematic risk factor models in consideration. As such, we report a CAPM alpha of 1.34% per month, a FF3 alpha of 1.10% per month and a FF5 alpha of 0.95% per month, all with strong statistical significance, as displayed by the respective t-stats of 10.86, 10.28 and 8.95 respectively. While the systematic risk factor models arguably do a reasonable job in explaining the observed excess returns on the high value portfolio P10, with the original excess return of 1.41% per month relating to a FF5 alpha of "only" 0.52%, they seem to fail at explaining the returns relating to the lowest value portfolio P1, which displayed a statistically insignificant excess return of 0.15% but shows a large negative and strongly statistically significant FF5 abnormal return of -0.43%. Given these observations we find that the strong performance of our zero-cost H-L portfolio does not only derive from the market underpricing company stocks that exhibit high value characteristics, as per our definition, but also from a tendency to overprice stocks that exhibit low value characteristics, especially when put into relation to proposed risk factor loadings of Fama and French (2015). However, while we find it striking that our strategy puts a lot of emphasis on a firm's gross profitability and the FF5 model seemingly has little added explanatory power over our reported abnormal returns, these observations do not necessarily collude with the notion of efficient markets, but could also hint at a miss-calibration of popular empirical asset pricing models. Still, mispricing through overconfidence, market under-reaction to the introduction of new information or other behavioral theories could likely also explain our observations.

3.6 Robustness Tests

In this section, we will conduct robustness tests to our proposed value investing strategy by changing rebalancing intervals, varying sample periods and alternating sample periods.

3.6.1 Robustness to Rebalancing Intervals

For this test (Table VI), we follow the same procedure as before for the actual strategy except that we adjust the rebalancing periods to 36 months for Panel A, 60 months for Panel B and 120 months for Panel C. We thus sort stocks only every third, fifth and tenth June respectively and calculate the corresponding returns for the subsequent 36, 60 and 120 months.

A look at Table VI shows that our observations in Table V are seemingly robust under different portfolio rebalancing conventions. The high z-score portfolios P7 to P10, as well as our zero-cost H-L portfolio exhibit large and statistically significant excess and abnormal returns in regards to the three chosen systematic risk factor models, irrespective of a decision to rebalance yearly or in three, five and ten year intervals. However, we do find that excess and abnormal returns somewhat diminish with prolonged rebalancing periods. This observation supports our original decision to rebalance portfolios every year. If we relate this finding to the persistence in value characteristics that decide our portfolio composition through derived z-scores, one could argue that the market prices these characteristics more efficiently over time. Still, the high z-score portfolios continuously offer higher excess returns than the low z-score portfolios, and they also maintain to be to a significant extent unexplained by the considered factor models.

Furthermore, we find that abnormal returns reported for the low to mid z-score portfolios, considering our z-score definition, largely loose statistical significance over time. For example, abnormal returns for the lowest z-score portfolio P1, while being highly statistically significant under our original rebalancing scenario, are completely statistically insignificant under a 10-year rebalancing regime. While we often find lower t-stats for our high z-score portfolios P7 to P10 and the zero-cost portfolio H-L corresponding to longer rebalancing periods, the abnormal returns remain highly statistically significant, as stated before. Thus, one might argue that high value characteristics and corresponding excess and abnormal returns are more persistent than the low z-score ones. Given that an increase in value characteristics could be interpreted as an effect of long-term shareholder value maximization strategies that ideally should dictate management decision making and therefore drive firms included in our low value characteristics portfolio to improve on the metrics we consider, among others, this observation is unsurprising.

As our value investing strategy can be described as a strategy that aims to incorporate information about the company's fundamental characteristics as immediately as possible for the most efficient portfolio generation, the robustness test on sample periods resulting in the 'deterioration' of excess and abnormal returns for prolonged rebalancing periods supports our decision to rebalance on a yearly basis to capture the highest rate of returns.

3.6.2 Robustness to Sample Periods

For this test (Table VII), we again follow the same procedure as before for the actual strategy except that we apply three different sample periods from July 1966 to December 1982 for Panel A, from July 1983 to December 1999 for Panel B and from July 2000 to December 2016 for Panel C.

Table VII offers some interesting insights, especially concerning the statistical significance of our observed excess and abnormal returns. Strikingly, while Panel A still displays large and statistically significant excess and abnormal returns of our zero-cost H-L portfolio over the CAPM and the FF3 model, the FF5 model seems to do a good job in explaining the observed abnormal returns for all portfolios. Even the FF3 model seems to explain most of the observed portfolio abnormal returns for the period between 1966 and 1982, while the H-L is still large and somewhat statistically significant.

In Panel B, we see a strong increase, both in size and statistical significance of abnormal returns measured for our portfolios over the FF3 and FF5 models, with the exception of the mid z-score portfolios P5 to P7. For the period between 1983 and 1999 we actually report the highest excess and abnormal returns for our zero-cost H-L portfolio, also with the highest statistical significance. Especially the FF3 and FF5 model fail to explain for example 0.74% and 0.70% monthly abnormal return for our highest z-score portfolio P10, even though the subsample period was covered in its entirety in the original study of the FF5 model.

Panel C again reports large and statistically significant excess and abnormal returns for our high value characteristic portfolios and the zero-cost portfolio H-L. While the excess returns, for example for the high z-score portfolio P10, are sometimes higher than in the previous subsample, the FF3 and FF5 models arguably do a marginally better job in explain those returns, though we still report 0.65% and 0.68% abnormal monthly returns for the high z-score portfolio P10 and even 1.04% and 0.80% abnormal monthly returns for the zero-cost H-L portfolio over the respective models. However, we also report a decrease in observed excess and abnormal returns for the lower z-score portfolios P1 to P5, most of which have only low or no statistical significance.

It is further interesting to see, that for the subsamples covering 1966 to 1982 and 1983 to 1999, excess and abnormal returns maintain a monotonically distribution. The same cannot entirely be said for the third subsample, covering the period between 2000 and 2016, as displayed in Panel C.

While excess returns are indeed monotonically distributed and increase in line with higher value characteristics of constructed portfolios, we report a certain diversion from this pattern when looking at the FF3 and FF5 abnormal returns for portfolios P2 to P4.

Overall, the low statistical significance of abnormal returns for the low value characteristic portfolios is somewhat puzzling, though we can maintain that our value investing strategy offers high and statistically significant excess and abnormal returns also over the subsample covering the years 2000 to 2016. While the returns are somewhat lower and less significant than for the second subsample covered in Panel B, the market seems to still inaccurately price value characteristics to date and the feasibility of our approach appears not to be undermined.

3.6.3 Robustness to Weighting Schemes

For this test (Table VIII), we again follow the same procedure as before for the actual strategy except that we weigh the indicator measures differently. We are trying to on the one hand cover possible weight distributions from a practitioner's point of view and on the other hand to keep them as simple and logical as possible. Panel A equally weighs the three categories inexpensiveness measures, profitability measures and supplementary measures so that the individual measures are weighted as $z_{multivariate} = 1/3 \times z_{b/m} + 1/3 \times z_{gpa} + 1/9 \times z_{eta} + 1/9 \times z_{cr} + 1/9 \times z_{gpgr}$. Panel B weighs inexpensiveness measures 40%, profitability measures 40% and supplementary measures 20% so that the individual measures are weighted as $z_{multivariate} = 0.4 \times z_{b/m} + 0.4 \times z_{gpa} + 1/15 \times z_{eta} + 1/15 \times z_{cr} + 1/15 \times z_{gpgr}$. Panel C equally weighs the two categories inexpensiveness measures and performance measures so that the individual measures are weighted as $z_{multivariate} = 0.5 \times z_{b/m} + 0.125 \times z_{gpa} + 0.125 \times z_{eta} + 0.125 \times z_{cr} + 0.125 \times z_{gpgr}$. Individual ratios are thus equally weighted within the specified categories for all panels. Replacing the composite z-score for each Panel allows us to follow the same steps as for the normal strategy.

Overall, we find that different weighting schemes display similar levels of size and statistical significance for excess and abnormal portfolio returns to those that we report in our original strategy (consider Table V for comparison). However, both excess and abnormal returns are marginally lower for alternative weighting schemes than in our core strategy. The highest and statistically most significant excess and abnormal returns are reported in Panel B for the weighting approach that equally weights inexpensiveness and profitability characteristics and a 20% weight for supplementary metrics. This weighting approach is thus the one most closely resembling our core strategy, in regards to returns. Among the three alternative weighting schemes it is also the one with the most statistically significant returns.

The alternative weighting scheme displayed in Panel A is the second closest to our original strategy, offering somewhat lower excess returns, but also somewhat higher abnormal returns over the FF3 and FF5 models for the high value characteristic portfolios P8 to P10 and the zero-cost portfolio H-L, at marginally higher statistical significance. It also displays a somewhat higher statistical significance of abnormal FF3 returns for the low value characteristic portfolios P1 and P2, and FF5 returns for P1 to P3.

Lastly, Panel C displays marginally lower excess returns than our original strategy, with marginally stronger statistically significance for the high z-score portfolio P10 and the zero-cost portfolio H-L, and lower statistical significance for the lower z-score portfolios P2 to P9. The lowest value characteristic portfolio P1 is again an outlier, showing higher excess returns with somewhat stronger, albeit still low, statistical significance compared to our original strategy, as displayed in Table V.

When looking solely on excess and abnormal returns of the zero-cost H-L portfolios for the different weighting schemes we are still convinced that our original strategy offers the best performance for value investors, however different weighting preferences can easily be accommodated at only marginal cost levels in terms of foregone excess and abnormal returns. Overall, our original strategy appears to hold up strongly.

3.6.4 Robustness to Size

For this test (Table IX), we again follow the same procedure as before for the actual strategy except that we only consider stocks with a market capitalization below 1 billion USD (small cap) for Panel A and above or equal 1 billion (mid and large cap) USD for Panel B.

For the small cap subsample in Panel A, we again find our strategy to hold up well, albeit with reduced statistical significance in comparison to our original strategy as displayed in Table V. Both excess and abnormal returns follow a largely monotonous distribution, with the sole exception being the statistically insignificant abnormal returns of low z-score portfolios P2 to P4 over the Fama & French (2015) five-factor model. Both, excess and abnormal returns for the high value characteristic portfolios P7 to P10 and the zero-cost portfolio H-L are large and statistically significant. For the mid z-score portfolios P5 and P6, we also report large excess and abnormal returns, albeit with a somewhat lower statistical significance.

Surprisingly, the same does not hold true for the mid and large cap subsample displayed in Panel B. While the reported excess returns have some statistical significance, it is comparatively low. Also, excess returns here do not follow a monotonous distribution. Especially for the mid to higher value characteristic portfolios P6 to P9, excess returns are largely in line, centering on 0.90% per month. Strikingly, the subsample of mid and large cap stocks is the only one for which we report the largest and statistically most significant abnormal returns in relation to the FF3 and FF5 models for the mid z-score portfolios. In every other sample, those portfolios usually exhibited one of the lowest statistical significances. Our zero-cost H-L portfolio also performs the weakest for the mid and large cap subsample, reporting abnormal returns of 0.19% and -0.06% per month for the FF3 and FF5 models respectively, with no statistical significance.

Thus, we must acknowledge that our strategy performs significantly better for small cap stocks than it does for large cap stocks. Fundamentally, that should not come as a surprise, given that small cap stocks generally receive little to no analyst exposure, which significantly reduces the news flow and makes information, though it is still publicly available, somewhat harder to come by. Also, small cap stocks potentially exhibit less concentration of institutional or other sophisticated investors, due to investment size restrictions, for example. As such, their pricing by the market can likely be interpreted as less efficient, though we still report higher excess and abnormal returns for higher value characteristic portfolios also among mid and large cap stocks, which as discussed previously still hints at an overpricing of low value and an underpricing of high value stocks, even though the Fama & French (2015) five-factor model seemingly does a good job in explaining returns for the mid to large cap subsample and potential mispricing is significantly less pronounced.

4. Conclusion

The paper at hand demonstrates that a portfolio strategy focused on a combination of value characteristics, which are identified by simple accounting-based fundamental analysis, can earn large and statistically significant excess and abnormal returns for investors in U.S. listed stocks, even over the newest adaptations of empirical asset pricing models focused on systematic risk factors. While we cannot claim to have found the most optimal financial ratios for the evaluation of the prospective performance of individual ‘value’ companies out of the complete universe of potential ratios at hand, we believe to have examined the most popular and, by testing them individually for their persistence and predictive power over future performance, identified a subset that is currently among the most likely to be beneficial to use for investors. As such, we chose a combination of metrics consisting of gross profit-to-assets for profitability, equity-to-assets for solvency, current ratio for liquidity, gross profit-to-assets-growth for growth and book-to-market ratio for inexpensiveness. By building zero-cost portfolios going long a portfolio including the stocks with the highest z-score based on selected value characteristics and simultaneously going short the portfolio obtained from including the stocks with the lowest z-score based on the same value characteristics, we report average monthly excess returns of 1.26%, over the whole sample period covering the time between July 1966 and December 2016. Figure 1 shows the cumulative gains on a USD 1 investment into our strategy that is held over the entire sample period. Figure 2 displays the monthly relative performance of our H-L portfolio versus the CRSP Equally Weighted Market Index. These returns are robust over time, as tested for different subsample periods, as well as for different selected weighting regimes and rebalancing periods. Results are furthermore robust for smaller capitalization firms, but somewhat less so for portfolios exclusively focused on companies with mid and large capitalization stocks. On this basis, we are fundamentally convinced that our results demonstrate an investor's ability to identify firms with either strong or poor future prospects, both in regards to operational and to stock price developments. Following our observation that firms exhibiting high value characteristics, as defined in our paper and measured by z-scores, offer statistically significant higher excess and abnormal returns than firms with lower value characteristics, there is reason to believe that value, as defined by us, is not adequately priced by the market. There could, however, be a risk characteristic specific to high value firms that is less strong in low value firms, which potentially explains this observation. As we do not intend to derive new risk factors, we cannot present a final answer to this puzzle.

Given that the financial data used for this paper is historical and the signals used and documented by this paper can be seen as somewhat dependent on previously documented results, there is a potential for the existence of a data dredging bias, which could limit the viability of our study. Such a bias, if existent, could negatively affect the predictive ability of displayed strategies if applied out-of-sample. Furthermore, we do not include transaction cost in our performance reporting. It would be interesting to examine how costly the implementation of the proposed strategy will be in practice. Especially if measured in regards to longer rebalancing periods, ways to decrease the impact of transaction costs could be determined. Here it seems important to note that excess and abnormal returns persist even under 5-year rebalancing schemes, though they are marginally lower than under shorter rebalancing intervals.

Further research could focus on a larger universe of financial ratios to assess whether the ones chosen in this paper are indeed these exhibiting the highest persistence and predictive power, or whether the universe of financial ratios offers even more convincing and strong metrics that should be included in the proposed portfolio formation strategy instead. Additionally, more research should be conducted focusing on the question of optimal portfolio weightings for the then chosen fundamental metrics. It would surely also be interesting to apply the strategy to different capital markets, for example the U.K., Germany or Japan, in order to assess its applicability in these different settings. Furthermore, value investing has been adapted to different asset classes, ranging from traditional assets such as bonds to alternative assets such as real estate. Thus, the proposed strategy that thus far only focuses on U.S. common stock could potentially be extended to incorporate financial stocks or to focus on completely different asset classes as well. Looking at the strategy's difference in robustness between small and large capitalization stock subsamples, an investor's ability to identify investment opportunities based on these criteria seems to be negatively correlated to the amount of news coverage stocks in consideration obtain, as well as to the number of savvy investors already holding investment positions. Whether this assessment holds true and what characteristics actually undermine the robustness of the strategy for a sample of mid and large capitalization stocks, should also be subject for future research. Lastly, while we briefly discussed the notion of market efficiency in the literature review section of this paper, based on our observations alone we cannot assess whether the findings display symptoms of market inefficiency or whether they instead develop as the product of a rational pricing strategy that simply appears to be anomalous. While the existing empirical asset pricing models chosen by us are unable to allocate observed abnormal returns to additional systematic risk factors, further research aimed at identifying more accurate risk factors or at enhancing the explanatory ability of the existing factors, could potentially explain our findings from a perspective of efficient risk-pricing.

Table I
Descriptive Statistics

This table reports summary statistics as of June each year, the month in which portfolios will be formed in subsequent tests. We differentiate between three samples, the full sample (1966-2016), the subsample I (1966-1991) and the subsample II (1992-2016). Within each sample and for each indicator measure, we show the time-series average of the cross-sectional average number of observations at the date of portfolio formation, the time-series average of the cross-sectional mean and the time-series average of the cross-sectional standard deviation. Our sample contains all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6) and we only consider sorting measures above zero.

Summary Statistics:	Full Sample (1966-2016)				Sub Sample I (1966-1991)				Sub Sample II (1992-2016)			
Sorting Metrics	Avg no Stocks	Mean	Std Dev	Coeff of Var	Avg no Stocks	Mean	Std Dev	Coeff of Var	Avg no Stocks	Mean	Std Dev	Coeff of Var
gross profits-to-assets	3537	0.39	0.27	0.69	3276	0.40	0.27	0.66	3831	0.38	0.28	0.73
return on capital employed	2823	0.30	4.90	16.47	2747	0.23	1.74	7.73	2908	0.38	8.45	22.32
return on equity	2696	0.46	7.81	16.92	2702	0.29	3.27	11.32	2689	0.66	12.92	19.69
gross profit margin	3025	0.16	0.41	2.56	2923	0.15	0.24	1.56	3139	0.17	0.61	3.55
EBITDA margin	3503	0.37	0.37	1.00	3259	0.33	0.17	0.51	3778	0.41	0.59	1.45
free cash flow-to-assets	2016	0.07	0.10	1.44	1775	0.06	0.08	1.41	2288	0.08	0.11	1.47
free cash flow-to-cap. empl.	2040	0.22	2.77	12.74	1786	0.15	1.51	10.10	2325	0.29	4.20	14.25
asset turnover	3716	1.25	1.01	0.81	3377	1.40	1.04	0.74	4097	1.09	0.98	0.90
working capital turnover	3185	13.38	105.10	7.85	2934	12.83	94.03	7.33	3468	14.00	117.54	8.39
equity-to-debt	3567	2.42	11.04	4.57	3262	2.27	14.90	6.57	3909	2.58	6.69	2.59
equity-to-assets	3580	0.53	0.22	0.41	3279	0.51	0.21	0.40	3919	0.55	0.23	0.42
current ratio	3623	3.12	9.24	2.96	3296	2.94	9.38	3.19	3992	3.32	9.09	2.74
cash-to-sales	3653	2.54	41.43	16.34	3319	0.77	15.74	20.48	4030	4.52	70.34	15.55
gross profit growth	2741	1.45	10.28	7.11	2444	1.31	6.56	5.00	3076	1.60	14.47	9.05
free cash flow growth	1865	4.78	50.94	10.66	1546	5.35	57.88	10.83	2223	4.14	43.13	10.41
book-to-market	3534	0.91	1.22	1.34	3220	1.02	0.89	0.87	3887	0.78	1.60	2.04
earnings-to-price	2598	0.09	0.13	1.42	2617	0.10	0.08	0.81	2577	0.08	0.18	2.37
free cash flow-to-price	1991	0.11	0.52	4.67	1743	0.12	0.42	3.53	2270	0.10	0.63	6.17

Table II
Fama-MacBeth Regressions

This table reports results from Fama-MacBeth regressions of returns on different performance measures as shown by the independent variables below. The cross-sectional regressions take the form $r_{tj} = \alpha_t + \beta_t' x_{tj} + \varepsilon_{tj}$ with r_{tj} as the return for stock j in month t, β_t $(n \times 1)$ as the vector of slope coefficients and x_{tj} $(n \times 1)$ as the vector of (lagged) independent variables for stock j in month t. In Panel A and B, each indicator measure is tested individually (univariate) and within the group of profitability and supplementary measures (multivariate). In Panel C, certain measures are regressed with controls following Novy-Marx (2013) for book-to-market (log(B/M)), size (log(market cap)) and past cumulative returns measured at horizons of one month ($r_{1,0}$) and twelve to two months ($r_{12,2}$). All independent variables are trimmed at the one and 99% levels. Our sample runs from July 1966 to December 2016 and contains all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6). We only consider performance measures above zero. Significance levels are shown by *** p<0.01, ** p<0.05 and * p<0.01.

Panel A: Profitability Metrics	slope coefficients (x10²) and [test-statistics] from cross-sectional regressions							
independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
gross profits-to-assets	0.81*** [6.49]							0.50*** [2.84]
return on capital employed		-0.22 [-1.05]						-0.57* [-1.69]
return on equity			-0.47** [-2.22]					-0.65** [-2.43]
gross profit margin				0.26 [1.21]				0.04 [0.12]
EBITDA margin					-0.65* [-1.70]			-0.27 [-0.45]
free cash flow-to-assets						0.31 [0.73]		-0.15 [-0.15]
free cash flow-to-capital employed							-0.29 [-1.31]	0.60 [0.90]

Panel B: Supplementary Metrics	slope coefficients (x10²) and [test-statistics] from cross-sectional regressions								
independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
asset turnover	0.19*** [3.91]								0.15*** [3.81]
working capital turnover		0.00 [-0.10]							0.00 [-0.09]
equity-to-debt			0.01 [0.48]						-0.03 [-1.53]
equity-to-assets				0.34** [1.97]					0.34 [1.38]
current ratio					0.02 [1.45]				0.03 [1.40]
cash-to-sales						0.06 [0.79]			0.21* [1.81]
gross profit growth							0.10*** [2.71]		0.07 [1.51]
free cash flow growth								0.00 [0.22]	0.00 [0.38]

Panel C: Combinations	slope coefficients (x10²) and [test-statistics] from cross-sectional regressions							
independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
gross profits-to-assets	0.96***				1.08***	0.90***	0.82***	0.83***
	[7.80]				[9.24]	[7.17]	[6.73]	[6.86]
asset turnover		0.13***			-0.06			-0.03
		[3.01]			[-1.60]			[-0.96]
equity-to-assets			0.43***			0.33**		0.23
			[2.94]			[2.29]		[1.61]
gross profit growth				0.10***			0.07**	0.07**
				[3.12]			[2.21]	[2.30]
log(B/M)	0.42***	0.36***	0.36***	0.30***	0.43***	0.41***	0.37***	0.36***
	[6.89]	[5.89]	[5.88]	[5.19]	[7.20]	[6.68]	[6.54]	[6.32]
log(market cap)	-0.09**	-0.10**	-0.11***	-0.10**	-0.09**	-0.09**	-0.07**	-0.08**
	[-2.12]	[-2.51]	[-2.60]	[-2.57]	[-2.18]	[-2.14]	[-1.96]	[-2.04]
$r_{1,0}$	-5.59***	-5.71***	-5.67***	-5.67***	-5.63***	-5.66***	-5.72***	-5.83***
	[-14.28]	[-14.51]	[-14.41]	[-14.59]	[-14.43]	[-14.56]	[-14.77]	[-15.17]
$r_{12,2}$	0.51***	0.51***	0.53***	0.50***	0.50***	0.50***	0.45**	0.43**
	[2.92]	[2.89]	[3.04]	[2.83]	[2.88]	[2.89]	[2.53]	[2.45]

Table III
Persistence of Performance Measures

This table reports average z-scores for different performance measures. Following Asness et. al. (2014), z-scores $z(x)$ for each indicator measure x are constructed by $z(x) = (r - \mu_r)/\sigma_r$, with r as the vector of ranks $r_i = rank(x_i)$, μ_r as the cross-sectional mean of r and σ_r as the cross-sectional standard deviation of r. Each June, stocks are sorted in ascending order based on their z-scores and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. For each performance measure, we report the time series average of the equally-weighted cross sectional means for the date of portfolio formation (t) and after five years (t + 60 months) maintaining the initial portfolio assignments. Our sample runs from June 1966 to December 2016 and contains all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6). We only consider performance measures above zero.

Panel A: Profitability Metrics		P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	P10-P1
GP-to-assets	t	-1.56	-1.26	-0.99	-0.69	-0.38	-0.05	0.30	0.66	1.06	1.50	3.06
	t + 60M	-1.08	-1.01	-0.73	-0.51	-0.28	-0.07	0.18	0.45	0.76	1.21	2.29
ROCE	t	-1.49	-1.07	-0.74	-0.44	-0.13	0.18	0.49	0.81	1.15	1.52	3.01
	t + 60M	-0.44	-0.43	-0.37	-0.31	-0.18	-0.05	0.09	0.24	0.42	0.70	1.15
ROE	t	-1.49	-1.07	-0.74	-0.43	-0.13	0.17	0.47	0.78	1.10	1.50	3.00
	t + 60M	-0.37	-0.39	-0.35	-0.28	-0.18	-0.12	0.01	0.13	0.31	0.54	0.91
EBITDA margin	t	-1.45	-0.97	-0.58	-0.23	0.10	0.41	0.72	1.02	1.30	1.59	3.04
	t + 60M	-0.94	-0.72	-0.51	-0.30	-0.10	0.08	0.34	0.62	0.97	1.33	2.28
GP margin	t	-1.55	-1.20	-0.89	-0.59	-0.29	0.01	0.32	0.65	1.02	1.47	3.02
	t + 60M	-1.18	-1.02	-0.78	-0.56	-0.35	-0.14	0.09	0.38	0.73	1.16	2.34
FCF-to-assets	t	-1.56	-1.21	-0.89	-0.57	-0.26	0.07	0.39	0.72	1.07	1.49	3.04
	t + 60M	-0.29	-0.31	-0.27	-0.23	-0.13	-0.05	0.05	0.20	0.30	0.52	0.81
FCF-to-CE	t	-1.56	-1.22	-0.90	-0.58	-0.25	0.07	0.39	0.72	1.07	1.49	3.05
	t + 60M	-0.30	-0.31	-0.28	-0.24	-0.14	-0.05	0.03	0.18	0.29	0.52	0.82

Panel B: Supplement. Metrics		P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	P10-P1
Asset turnover	t	-1.50	-1.12	-0.82	-0.52	-0.23	0.07	0.38	0.72	1.09	1.51	3.01
	t + 60M	-1.19	-0.85	-0.52	-0.27	-0.05	0.15	0.36	0.57	0.84	1.29	2.48
WC turnover	t	-1.33	-0.74	-0.40	-0.10	0.19	0.47	0.76	1.03	1.31	1.59	2.92
	t + 60M	-0.77	-0.38	-0.18	0.01	0.19	0.38	0.58	0.76	0.95	1.15	1.92
Equity-to-debt	t	-1.53	-1.19	-0.92	-0.66	-0.40	-0.15	0.12	0.41	0.77	1.35	2.88
	t + 60M	-0.95	-0.80	-0.66	-0.51	-0.35	-0.20	-0.04	0.14	0.38	0.79	1.74
Equity-to-assets	t	-1.53	-1.19	-0.91	-0.64	-0.37	-0.11	0.16	0.46	0.81	1.37	2.90
	t + 60M	-0.93	-0.81	-0.64	-0.48	-0.32	-0.16	-0.01	0.16	0.39	0.79	1.72
Current ratio	t	-1.57	-1.27	-0.97	-0.66	-0.37	-0.09	0.20	0.50	0.84	1.38	2.95
	t + 60M	-1.13	-0.90	-0.63	-0.41	-0.22	-0.07	0.09	0.26	0.43	0.74	1.87
Cash-to-sales	t	-1.55	-1.23	-0.95	-0.68	-0.41	-0.13	0.15	0.45	0.79	1.35	2.90
	t + 60M	-0.90	-0.76	-0.64	-0.51	-0.40	-0.27	-0.15	0.02	0.25	0.77	1.67
GP growth	t	-1.50	-1.10	-0.78	-0.48	-0.19	0.09	0.38	0.68	1.01	1.46	2.96
	t + 60M	0.19	0.04	0.00	-0.02	-0.04	-0.07	-0.07	-0.08	-0.09	-0.07	-0.26
FCF growth	t	-1.51	-1.12	-0.77	-0.43	-0.12	0.18	0.48	0.79	1.14	1.52	3.04
	t + 60M	0.06	0.07	0.04	0.04	-0.02	-0.04	-0.03	-0.03	0.01	0.00	-0.05

Table IV
Univariate Strategies

This table reports monthly excess returns ($E[r^e]$), monthly abnormal returns (α), annualized Sharpe ratios and annualized Information ratios for long-short extreme decile portfolios (H-L) of strategies formed by sorting on indicator measures. In each June and for each measure, stocks are sorted in ascending order based on their measure and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. We then calculate equally weighted returns for each decile portfolio for every of the subsequent 12 months, starting in July of the same year and ending in June of the following year. For each measure, we report the time series average of the long-short extreme decile portfolios' (H-L) monthly excess returns. Furthermore, we show monthly abnormal returns relative to the CAPM, FF3 and FF5 model, annualized Sharpe and Information ratios. Our sample runs from July 1966 to December 2016 and contains all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6). We only consider performance measures above zero. Significance levels are shown by *** p<0.01, ** p<0.05 and * p<0.01.

Panel A: Profitability Strategies	$E[r^e]$	α_{CAPM}	α_{FF3}	α_{FF5}	Sharpe Ratio	Information Ratio
gross profits-to-assets	0.79***	0.76***	0.79***	0.51***	0.98	0.75
	[6.99]	[6.70]	[6.94]	[5.09]		
return on capital employed	-0.07	-0.07	0.15*	0.04	-0.10	0.07
	[-0.73]	[-0.70]	[1.74]	[0.45]		
return on equity	-0.26***	-0.32***	-0.15*	-0.11	-0.38	-0.19
	[-2.69]	[-3.43]	[-1.74]	[-1.25]		
gross profit margin	0.12	0.07	0.36***	0.49***	0.15	0.82
	[1.04]	[0.66]	[3.91]	[5.53]		
EBITDA margin	-0.29*	-0.21	-0.08	-0.11	-0.25	-0.12
	[-1.80]	[-1.30]	[-0.56]	[-0.79]		
free cash flow-to-assets	0.03	0.03	0.16**	0.23***	0.06	0.48
	[0.43]	[0.41]	[2.32]	[3.24]		
free cash flow-to-capital employed	-0.05	-0.07	0.07	0.20**	-0.08	0.37
	[-0.54]	[-0.81]	[0.88]	[2.51]		

Panel B: Supplement. Strategies	$E[r^e]$	α_{CAPM}	α_{FF3}	α_{FF5}	Sharpe Ratio	Information Ratio
asset turnover	0.63***	0.65***	0.48***	0.04	0.54	0.05
	[3.83]	[3.95]	[2.96]	[0.32]		
working capital turnover	0.06	0.19	-0.02	-0.34***	0.05	-0.58
	[0.38]	[1.36]	[-0.17]	[-3.91]		
equity-to-debt	0.28**	0.32***	0.56***	0.70***	0.35	1.16
	[2.52]	[2.84]	[5.94]	[7.80]		
equity-to-assets	0.28***	0.32***	0.56***	0.67***	0.37	1.14
	[2.64]	[2.99]	[6.12]	[7.70]		
current ratio	0.44***	0.31**	0.46***	0.62***	0.47	0.93
	[3.32]	[2.48]	[4.69]	[6.25]		
cash-to-sales	-0.02	-0.14	0.15	0.51***	-0.02	0.81
	[-0.12]	[-0.94]	[1.20]	[5.46]		
gross profit growth	0.44***	0.46***	0.50***	0.41***	0.81	0.79
	[5.72]	[6.08]	[6.56]	[5.33]		
free cash flow growth	0.11	0.09	0.10	0.13*	0.21	0.26
	[1.52]	[1.25]	[1.41]	[1.77]		

Panel C: Valuation Strategies	$E[r^e]$	α_{CAPM}	α_{FF3}	α_{FF5}	Sharpe Ratio	Information Ratio
book-to-market	1.12***	1.29***	0.79***	0.56***	0.92	0.79
	[6.53]	[7.97]	[7.24]	[5.33]		
earnings-to-price	0.66***	0.78***	0.50***	0.31***	0.75	0.54
	[5.35]	[6.76]	[5.55]	[3.62]		
free cash flow-to-price	0.62***	0.71***	0.43***	0.33***	0.75	0.52
	[5.32]	[6.31]	[4.68]	[3.51]		

Table V
Multivariate Strategy

This table reports average excess returns, abnormal returns, Sharpe ratios and Information ratios to a multivariate strategy based on different performance and inexpensiveness measures. Following Asness et. al. (2014), z-scores $z(x)$ for each indicator measure x are constructed by $z(x) = (r - \mu_r)/\sigma_r$, with r as the vector of ranks $r_i = rank(x_i)$, μ_r as the cross-sectional mean of r and σ_r as the cross-sectional standard deviation of r. We weight the z-scores with 60% for performance and 40% for inexpensiveness measures. Within the performance measures, we apply 50% to profitability, 25% to financial stability and 25% to growth. The measures include book-to-market for inexpensiveness, gross profits-to-assets for profitability, equity-to-debt and current ratio for financial stability (equally weighted) and growth in gross profits (scaled by assets) for growth. In each June, stocks are sorted in ascending order based on their composite z-score and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. We then calculate equally weighted returns for each decile portfolio for every of the subsequent 12 months, starting in July of the same year and ending in June of the following year. For each portfolio, we report the time series average of the monthly excess returns, abnormal returns relative to the Fama-French three-factor and five-factor models, Sharpe ratios and Information ratios. Our sample runs from July 1966 to December 2016 and contains all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6). We only consider performance measures above zero. Significance levels are shown by *** p<0.01, ** p<0.05 and * p<0.01.

Value Investing Strategy	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.15	0.52**	0.56**	0.62***	0.76***	0.88***	0.99***	1.09***	1.20***	1.41***	1.26***
	[0.59]	[2.30]	[2.50]	[2.73]	[3.41]	[3.78]	[4.19]	[4.47]	[4.92]	[5.66]	[9.94]
CAPM alpha	-0.47***	-0.04	0.00	0.05	0.21**	0.32***	0.42***	0.52***	0.64***	0.88***	1.34***
	[-3.61]	[-0.43]	[0.02]	[0.55]	[2.10]	[2.79]	[3.58]	[3.96]	[4.64]	[5.55]	[10.86]
FF3 alpha	-0.55***	-0.16**	-0.13*	-0.11*	0.04	0.12*	0.21***	0.27***	0.35***	0.55***	1.10***
	[-5.22]	[-2.05]	[-1.78]	[-1.77]	[0.71]	[1.75]	[2.96]	[3.67]	[4.76]	[6.15]	[10.28]
FF5 alpha	-0.43***	-0.15*	-0.13*	-0.13**	0.03	0.11	0.19***	0.24***	0.33***	0.52***	0.95***
	[-4.10]	[-1.90]	[-1.74]	[-1.99]	[0.44]	[1.63]	[2.74]	[3.21]	[4.35]	[5.62]	[8.95]
Sharpe Ratio	0.08	0.32	0.35	0.38	0.48	0.53	0.59	0.63	0.69	0.80	1.40
Information Ratio	-0.61	-0.28	-0.26	-0.29	0.07	0.24	0.41	0.48	0.64	0.83	1.33

Table VI
Robustness to Rebalancing Intervals

This table reports average excess returns, abnormal returns, Sharpe ratios and Information ratios to the multivariate strategy proposed in Table V with the additional rebalancing intervals 36 months, 60 months and 120 months. For Panel A, B and C stocks are sorted every third, fifth and tenth June respectively in ascending order based on their composite z-score and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. We then calculate equally weighted returns for each decile portfolio for every of the subsequent 36 months, 60 months and 120 months. For each portfolio, we report the time series average of the monthly excess returns, abnormal returns relative to the Fama-French three-factor and five-factor models, Sharpe ratios and Information ratios. Our sample runs from July 1966 to December 2016 and contains all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6). We only consider performance measures above zero. Significance levels are shown by *** p<0.01, ** p<0.05 and * p<0.01.

Panel A: 36M Rebalancing	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.27	0.55**	0.69***	0.69***	0.75***	0.89***	0.99***	1.04***	1.11***	1.28***	1.01***
	[1.04]	[2.40]	[3.07]	[3.09]	[3.40]	[3.93]	[4.28]	[4.39]	[4.61]	[5.22]	[8.62]
CAPM alpha	-0.34***	-0.01	0.13	0.14	0.20**	0.33***	0.44***	0.48***	0.55***	0.75***	1.09***
	[-2.58]	[-0.11]	[1.34]	[1.39]	[2.07]	[3.21]	[3.79]	[3.89]	[4.21]	[4.89]	[9.50]
FF3 alpha	-0.48***	-0.18**	-0.03	-0.03	0.03	0.14**	0.22***	0.25***	0.29***	0.45***	0.94***
	[-4.63]	[-2.21]	[-0.49]	[-0.56]	[0.45]	[2.38]	[3.24]	[3.45]	[4.00]	[5.06]	[8.74]
FF5 alpha	-0.43***	-0.23***	-0.10	-0.06	0.00	0.11*	0.21***	0.25***	0.27***	0.43***	0.86***
	[-4.01]	[-2.70]	[-1.34]	[-1.00]	[0.08]	[1.83]	[2.95]	[3.38]	[3.60]	[4.66]	[7.84]
Sharpe Ratio	0.15	0.34	0.43	0.44	0.48	0.55	0.60	0.62	0.65	0.73	1.21
Information Ratio	-0.59	-0.40	-0.20	-0.15	0.01	0.27	0.44	0.50	0.53	0.69	1.16

Panel B: 60M Rebalancing	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.34	0.61***	0.67***	0.74***	0.79***	0.89***	1.01***	1.04***	1.13***	1.19***	0.85***
	[1.39]	[2.79]	[2.99]	[3.39]	[3.59]	[4.00]	[4.35]	[4.49]	[4.79]	[4.98]	[7.42]
CAPM alpha	-0.24*	0.07	0.11	0.20**	0.24**	0.35***	0.45***	0.49***	0.58***	0.67***	0.91***
	[-1.86]	[0.74]	[1.15]	[2.05]	[2.54]	[3.33]	[3.94]	[4.09]	[4.59]	[4.56]	[7.99]
FF3 alpha	-0.40***	-0.10	-0.09	0.01	0.06	0.15**	0.23***	0.26***	0.33***	0.38***	0.78***
	[-3.87]	[-1.29]	[-1.32]	[0.18]	[0.88]	[2.46]	[3.28]	[3.80]	[4.61]	[4.35]	[7.22]
FF5 alpha	-0.32**	-0.12	-0.12*	-0.03	0.01	0.09	0.20***	0.21***	0.28***	0.31***	0.63***
	[-3.09]	[-1.47]	[-1.75]	[-0.56]	[0.12]	[1.45]	[2.82]	[3.01]	[3.87]	[3.49]	[5.97]
Sharpe Ratio	0.19	0.39	0.42	0.48	0.51	0.56	0.61	0.63	0.67	0.70	1.04
Information Ratio	-0.46	-0.22	-0.26	-0.08	0.02	0.22	0.42	0.45	0.57	0.52	0.88

Panel C: 120M Rebalancing	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.58**	0.76***	0.78***	0.80***	0.80***	0.88***	0.99***	0.98***	1.01***	1.09***	0.51***
	[2.54]	[3.67]	[3.63]	[3.80]	[3.79]	[4.06]	[4.37]	[4.38]	[4.31]	[4.64]	[4.62]
CAPM alpha	0.04	0.25***	0.24***	0.27***	0.27***	0.34***	0.44***	0.45***	0.45***	0.56***	0.52***
	[0.37]	[2.66]	[2.67]	[3.09]	[3.10]	[3.60]	[4.11]	[3.94]	[3.74]	[4.08]	[4.68]
FF3 alpha	-0.12	0.07	0.06	0.11*	0.10*	0.18***	0.23***	0.22***	0.21***	0.30***	0.41***
	[-1.17]	[0.93]	[0.94]	[1.80]	[1.69]	[3.03]	[3.43]	[3.38]	[3.05]	[3.56]	[3.92]
FF5 alpha	-0.03	0.05	0.02	0.03	0.04	0.10*	0.22***	0.18***	0.18**	0.23***	0.26**
	[-0.26]	[0.62]	[0.24]	[0.44]	[0.57]	[1.77]	[3.05]	[2.68]	[2.55]	[2.72]	[2.48]
Sharpe Ratio	0.36	0.52	0.51	0.54	0.53	0.57	0.61	0.62	0.61	0.65	0.65
Information Ratio	-0.04	0.09	0.04	0.07	0.08	0.26	0.45	0.40	0.38	0.40	0.37

Table VII
Robustness to Sample Periods

This table reports average excess returns, abnormal returns, Sharpe ratios and Information ratios to the multivariate strategy proposed in Table V with alternating sample periods. In each June, stocks are sorted in ascending order based on their composite z-score and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. We then calculate equally weighted returns for each decile portfolio for every of the subsequent 12 months, starting in July of the same year and ending in June of the following year. For each portfolio, we report the time series average of the monthly excess returns, abnormal returns relative to the Fama-French three-factor and five-factor models, Sharpe ratios and Information ratios. Our sample runs from July 1966 to December 1982 for Panel A, July 1983 to December 1999 for Panel B and July 2000 to December 2016 for Panel C. All samples contain all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6). We only consider performance measures above zero. Significance levels are shown by *** $p<0.01$, ** $p<0.05$ and * $p<0.01$.

Panel A: 1966-1982	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.16	0.42	0.38	0.56	0.70	0.78*	0.99**	0.99**	1.06**	1.22**	1.06***
	[0.35]	[1.01]	[0.88]	[1.27]	[1.56]	[1.70]	[2.13]	[2.07]	[2.20]	[2.47]	[4.02]
CAPM alpha	-0.06	0.22	0.17	0.35**	0.48***	0.57***	0.77***	0.77***	0.85***	1.01***	1.07***
	[-0.30]	[1.41]	[1.08]	[2.02]	[2.76]	[2.71]	[3.52]	[3.09]	[3.10]	[3.37]	[4.07]
FF3 alpha	-0.28*	-0.09	-0.16*	-0.04	0.10	0.06	0.23**	0.11	0.14	0.23**	0.51**
	[-1.77]	[-0.86]	[-1.92]	[-0.55]	[1.15]	[0.70]	[2.53]	[1.20]	[1.37]	[1.96]	[2.56]
FF5 alpha	-0.09	-0.01	-0.14	-0.06	0.08	0.02	0.13	0.04	0.04	0.08	0.17
	[-0.60]	[-0.13]	[-1.63]	[-0.78]	[0.86]	[0.20]	[1.48]	[0.38]	[0.39]	[0.68]	[0.93]
Sharpe Ratio	0.09	0.25	0.22	0.31	0.39	0.42	0.52	0.51	0.54	0.61	0.99
Information Ratio	-0.16	-0.03	-0.43	-0.21	0.23	0.05	0.39	0.10	0.10	0.18	0.25

Panel B: 1983-1999	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	-0.14	0.35	0.44	0.39	0.59*	0.77**	0.80**	0.96***	1.03***	1.30***	1.44***
	[-0.34]	[0.99]	[1.26]	[1.20]	[1.81]	[2.31]	[2.29]	[2.71]	[2.96]	[3.76]	[9.81]
CAPM alpha	-1.07***	-0.54***	-0.45***	-0.45***	-0.26*	-0.07	-0.06	0.10	0.18	0.55**	1.62***
	[-4.53]	[-2.96]	[-2.60]	[-2.84]	[-1.65]	[-0.43]	[-0.34]	[0.49]	[0.92]	[2.31]	[11.92]
FF3 alpha	-0.84***	-0.37***	-0.34***	-0.31***	-0.12	0.08	0.08	0.33***	0.35***	0.74***	1.59***
	[-5.52]	[-2.90]	[-2.81]	[-3.08]	[-1.22]	[0.90]	[0.76]	[3.25]	[3.39]	[5.60]	[11.49]
FF5 alpha	-0.82***	-0.38***	-0.33***	-0.35***	-0.13	0.03	0.03	0.25**	0.28***	0.70***	1.52***
	[-5.48]	[-2.88]	[-2.75]	[-3.50]	[-1.32]	[0.30]	[0.23]	[2.43]	[2.62]	[5.13]	[11.16]
Sharpe Ratio	-0.08	0.24	0.31	0.30	0.44	0.57	0.56	0.67	0.73	0.93	2.42
Information Ratio	-1.46	-0.77	-0.74	-0.93	-0.35	0.08	0.06	0.65	0.70	1.37	2.98

Panel C: 2000-2016	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.22	0.70*	0.71*	0.76*	0.84**	0.93**	1.03**	1.14***	1.28***	1.46***	1.24***
	[0.44]	[1.67]	[1.75]	[1.85]	[2.13]	[2.20]	[2.45]	[2.60]	[2.97]	[3.26]	[5.41]
CAPM alpha	-0.33	0.22	0.25	0.29*	0.40**	0.47**	0.57***	0.66***	0.83***	1.00***	1.34***
	[-1.56]	[1.37]	[1.53]	[1.82]	[2.38]	[2.38]	[2.94]	[3.09]	[3.63]	[3.90]	[6.22]
FF3 alpha	-0.38**	0.12	0.13	0.11	0.20*	0.24*	0.34***	0.39***	0.50***	0.65***	1.04***
	[-2.13]	[0.96]	[1.00]	[0.94]	[1.65]	[1.81]	[2.67]	[2.70]	[3.27]	[3.46]	[5.85]
FF5 alpha	-0.12	0.19	0.18	0.16	0.22*	0.28**	0.41***	0.40***	0.53***	0.68***	0.80***
	[-0.66]	[1.41]	[1.31]	[1.38]	[1.79]	[1.99]	[3.02]	[2.67]	[3.33]	[3.40]	[4.46]
Sharpe Ratio	0.11	0.41	0.43	0.46	0.52	0.54	0.60	0.64	0.73	0.80	1.33
Information Ratio	-0.17	0.37	0.35	0.36	0.47	0.52	0.80	0.70	0.88	0.90	1.18

Table VIII
Robustness to Indicator Measure Weights

This table reports average excess returns, abnormal returns, Sharpe ratios and Information ratios to the multivariate strategy proposed in Table V with alternating composite z-scores. Panel A equally weighs the three categories inexpensiveness measures, profitability measures and supplementary measures. Panel B weighs inexpensiveness measures 40%, profitability measures 40% and supplementary measures 20%. Panel C equally weighs the two categories inexpensiveness measures and performance measures. Individual ratios are equally weighted within the specified categories for all panels. In each June, stocks are sorted in ascending order based on their composite z-score and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. We then calculate equally weighted returns for each decile portfolio for every of the subsequent 12 months, starting in July of the same year and ending in June of the following year. For each portfolio, we report the time series average of the monthly excess returns, abnormal returns relative to the Fama-French three-factor and five-factor models, Sharpe ratios and Information ratios. Our sample runs from July 1966 to December 2016 and contains all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6). We only consider performance measures above zero. Significance levels are shown by *** p<0.01, ** p<0.05 and * p<0.01.

Panel A: 1/3-1/3-1/3	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.15	0.50**	0.62***	0.70***	0.72***	0.91***	0.91***	1.06***	1.13***	1.40***	1.24***
	[0.61]	[2.29]	[2.74]	[3.05]	[3.03]	[3.83]	[3.82]	[4.36]	[4.65]	[5.71]	[10.33]
CAPM alpha	-0.44***	-0.04	0.07	0.14	0.14	0.33***	0.34***	0.49***	0.57***	0.86***	1.30***
	[-3.41]	[-0.40]	[0.63]	[1.28]	[1.25]	[2.93]	[2.85]	[3.81]	[4.23]	[5.72]	[10.87]
FF3 alpha	-0.55***	-0.21***	-0.12	-0.05	-0.05	0.14**	0.13**	0.27***	0.32***	0.57***	1.12***
	[-5.17]	[-2.65]	[-1.52]	[-0.76]	[-0.62]	[2.05]	[1.96]	[3.65]	[4.38]	[6.75]	[10.44]
FF5 alpha	-0.47***	-0.18**	-0.17**	-0.07	-0.06	0.12*	0.13*	0.26***	0.30***	0.55***	1.01***
	[-4.29]	[-2.28]	[-2.03]	[-0.94]	[-0.82]	[1.75]	[1.88]	[3.46]	[4.06]	[6.25]	[9.29]
Sharpe Ratio	0.09	0.32	0.39	0.43	0.43	0.54	0.54	0.61	0.65	0.80	1.45
Information Ratio	-0.64	-0.34	-0.30	-0.14	-0.12	0.26	0.28	0.51	0.60	0.93	1.38

Panel B: 40-40-20	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.16	0.48**	0.57***	0.69***	0.71***	0.83***	0.99***	1.08***	1.19***	1.41***	1.25***
	[0.63]	[2.17]	[2.63]	[3.07]	[3.07]	[3.52]	[4.11]	[4.42]	[4.93]	[5.68]	[9.48]
CAPM alpha	-0.45***	-0.07	0.03	0.14	0.14	0.26**	0.41***	0.50***	0.64***	0.88***	1.33***
	[-3.46]	[-0.68]	[0.32]	[1.33]	[1.33]	[2.28]	[3.45]	[3.89]	[4.70]	[5.58]	[10.21]
FF3 alpha	-0.53***	-0.21***	-0.14**	-0.04	-0.04	0.07	0.20***	0.27***	0.37***	0.56***	1.09***
	[-4.83]	[-2.65]	[-2.01]	[-0.52]	[-0.54]	[1.06]	[2.78]	[3.82]	[5.01]	[6.19]	[9.59]
FF5 alpha	-0.40***	-0.22***	-0.15**	-0.05	-0.05	0.06	0.16**	0.27***	0.33***	0.53***	0.93***
	[-3.67]	[-2.69]	[-2.09]	[-0.63]	[-0.68]	[0.81]	[2.27]	[3.71]	[4.42]	[5.70]	[8.28]
Sharpe Ratio	0.09	0.31	0.37	0.43	0.43	0.50	0.58	0.62	0.69	0.80	1.33
Information Ratio	-0.54	-0.40	-0.31	-0.09	-0.10	0.12	0.34	0.55	0.65	0.84	1.23

Panel C: 50.0-12.5-37.5	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.28	0.53**	0.54**	0.71***	0.73***	0.88***	1.02***	1.04***	1.16***	1.41***	1.14***
	[1.07]	[2.21]	[2.31]	[3.09]	[3.20]	[3.89]	[4.41]	[4.40]	[4.69]	[5.79]	[9.61]
CAPM alpha	-0.34***	-0.07	-0.05	0.14	0.17	0.34***	0.47***	0.49***	0.61***	0.90***	1.24***
	[-2.67]	[-0.71]	[-0.50]	[1.39]	[1.61]	[3.02]	[3.92]	[3.81]	[4.16]	[5.69]	[10.95]
FF3 alpha	-0.41***	-0.12	-0.12*	0.02	0.00	0.12*	0.19***	0.21***	0.27***	0.56***	0.97***
	[-4.08]	[-1.48]	[-1.67]	[0.36]	[-0.02]	[1.95]	[2.92]	[2.90]	[3.43]	[6.16]	[10.49]
FF5 alpha	-0.36***	-0.08	-0.08	0.03	-0.01	0.10	0.18***	0.22***	0.24***	0.53***	0.90***
	[-3.54]	[-1.01]	[-1.15]	[0.38]	[-0.13]	[1.54]	[2.69]	[2.96]	[2.96]	[5.66]	[9.48]
Sharpe Ratio	0.15	0.31	0.32	0.44	0.45	0.55	0.62	0.62	0.66	0.81	1.35
Information Ratio	-0.52	-0.15	-0.17	0.06	-0.02	0.23	0.40	0.44	0.44	0.84	1.40

Table IX
Robustness to Size

This table reports average excess returns, abnormal returns, Sharpe ratios and Information ratios to the multivariate strategy proposed in Table V differentiated between small cap stocks (<1bn) and mid/large cap stocks (>=1bn). In each June, stocks are sorted in ascending order based on their composite z-score and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. We then calculate equally weighted returns for each decile portfolio for every of the subsequent 12 months, starting in July of the same year and ending in June of the following year. For each portfolio, we report the time series average of the monthly excess returns, abnormal returns relative to the Fama-French three-factor and five-factor models, Sharpe ratios and Information ratios. Our sample runs from July 1966 to December 2016 and contains all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6). For Panel A and B, we limit stocks to below 1 billion USD market capitalization and above or equal 1 billion USD market capitalization respectively. We only consider performance measures above zero. Significance levels are shown by *** p<0.01, ** p<0.05 and * p<0.01.

Panel A: Small Cap	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.17	0.75	0.80*	0.80*	1.09**	1.12**	1.38***	1.39***	1.28***	1.73***	1.56***
	[0.32]	[1.60]	[1.76]	[1.80]	[2.41]	[2.45]	[2.99]	[3.14]	[2.90]	[3.64]	[5.90]
CAPM alpha	-0.34	0.29	0.36	0.37	0.67**	0.67***	0.95***	0.97***	0.87***	1.31***	1.66***
	[-1.22]	[1.15]	[1.43]	[1.47]	[2.48]	[2.70]	[3.45]	[3.81]	[3.28]	[4.13]	[6.57]
FF3 alpha	-0.51**	0.00	0.03	0.08	0.38*	0.36**	0.57***	0.61***	0.51**	0.90***	1.41***
	[-2.14]	[0.01]	[0.19]	[0.39]	[1.84]	[1.96]	[2.86]	[3.45]	[2.52]	[3.61]	[5.98]
FF5 alpha	-0.24	0.12	0.13	0.12	0.50**	0.39**	0.61***	0.65***	0.50**	0.97***	1.21***
	[-0.99]	[0.57]	[0.70]	[0.58]	[2.34]	[2.03]	[2.93]	[3.54]	[2.37]	[3.72]	[4.97]
Sharpe Ratio	0.08	0.39	0.43	0.44	0.58	0.59	0.73	0.76	0.70	0.88	1.43
Information Ratio	-0.26	0.15	0.18	0.15	0.61	0.53	0.76	0.92	0.61	0.96	1.29

Panel B: Mid & Large Cap	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	H-L
Excess return	0.55	0.69*	0.59	0.70**	0.80**	0.87**	0.88**	0.92**	0.88**	1.00**	0.45*
	[1.16]	[1.83]	[1.63]	[2.00]	[2.17]	[2.38]	[2.35]	[2.44]	[2.25]	[2.35]	[1.93]
CAPM alpha	0.04	0.28**	0.20	0.32**	0.40***	0.47***	0.47***	0.52***	0.47***	0.57***	0.53**
	[0.23]	[1.96]	[1.43]	[2.47]	[2.90]	[3.61]	[3.31]	[3.48]	[2.77]	[2.68]	[2.35]
FF3 alpha	0.10	0.28*	0.14	0.27**	0.31**	0.37***	0.29**	0.34**	0.27*	0.29	0.19
	[0.53]	[1.89]	[1.00]	[2.10]	[2.29]	[2.93]	[2.33]	[2.55]	[1.76]	[1.57]	[1.08]
FF5 alpha	0.19	0.16	-0.04	0.14	0.23	0.24*	0.17	0.18	0.06	0.13	-0.06
	[1.02]	[1.05]	[-0.26]	[1.05]	[1.62]	[1.89]	[1.33]	[1.40]	[0.43]	[0.73]	[-0.32]
Sharpe Ratio	0.28	0.44	0.39	0.48	0.53	0.58	0.57	0.59	0.55	0.57	0.47
Information Ratio	0.26	0.27	-0.07	0.27	0.42	0.49	0.34	0.36	0.11	0.19	-0.08

Figure 1
Cumulative Performance

Figure I displays the performance, measured in paper excess returns over the one month U.S. Treasury Bill rate, of a USD 1 investment in our H-L portfolio undertaken end of June 1966 and held until December 2016. The USD 1 invested in our H-L portfolio translate into a gain of USD 1465.20 over the holding period.

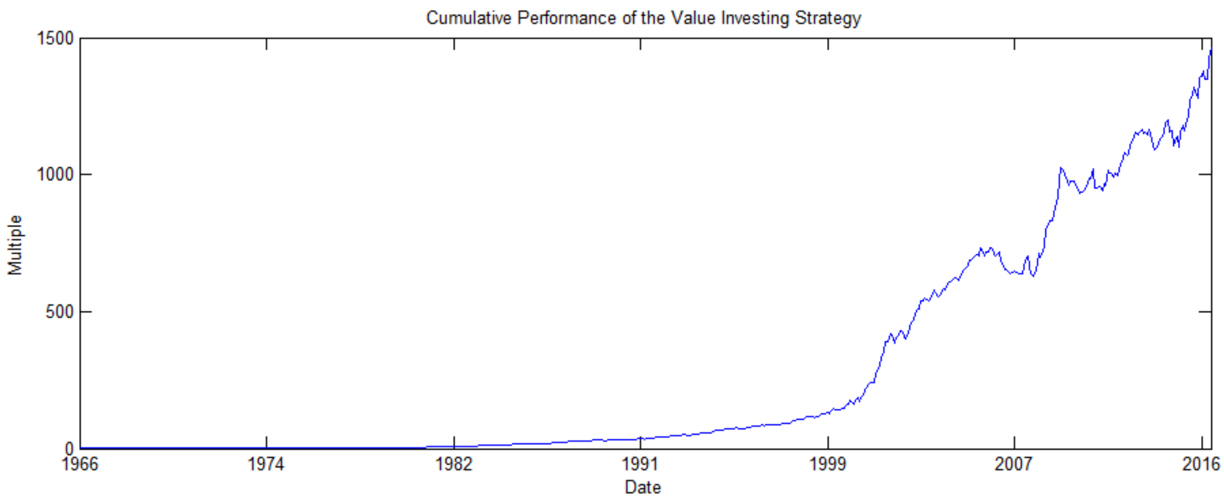
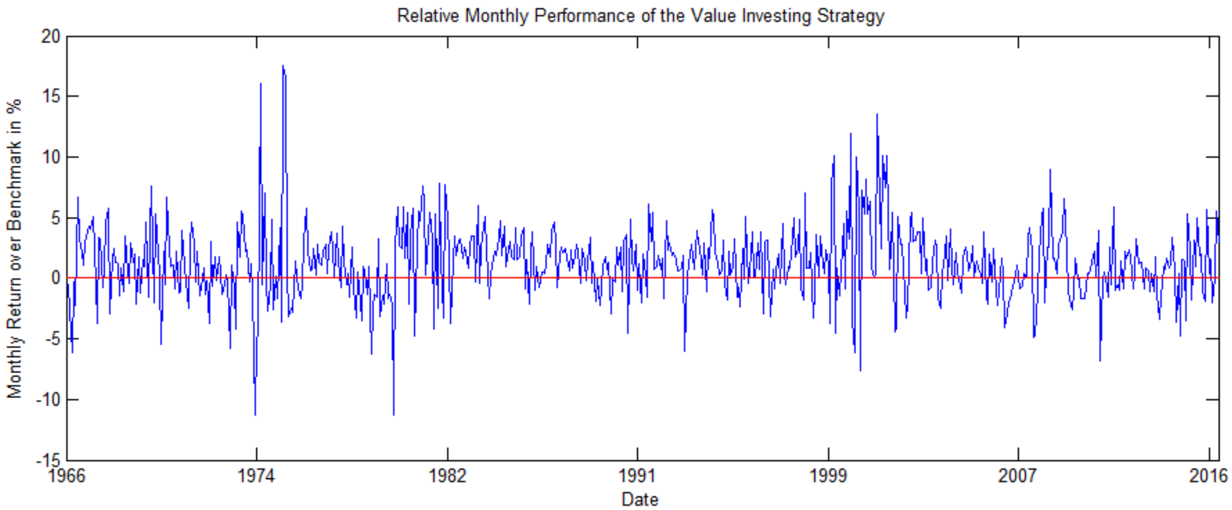


Figure 2
Relative Monthly Performance

Figure II displays the relative monthly performance, measured in excess returns over the one month U.S. Treasury Bill rate, of our H-L portfolio compared to the CRSP Equally Weighted Market Index. The observed period covers June 1966 to December 2016.



References

Abarbanell, J.S., & Bushee, B.J. (1998). Abnormal Returns to a Fundamental Analysis Strategy. *The Accounting Review, 73, 1,* 19-45.

Aharoni, G., Grundy, B., & Zeng, Q. (2013). Stock returns and the Miller Modigliani valuation formula: Revisiting the Fama French analysis. *Journal of Financial Economics, 110, 2*, 347-357.

Ang, A., & Chen, J. (2005). CAPM over the long run: 1926–2001. *Journal of Empirical Finance, 14, 1,* 1-40.

Asness, C.S., Frazzini, A., & Petersen, L.H. (2014). Quality Minus Junk.

Bachelier, L. (1900). The Theory of Speculation. *Annales scientifiques de l'Ecole Normale Superieure, 3, 17,* 21-86.

Banz, R.W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics, 9, 1,* 3-18.

Barber, B.M., & Odean, T. (2001). Boys will be Boys: Gender, Overconfidence, and Common Stock Investment. *The Quarterly Journal of Economics, 116, 1,* 261-292.

Basu, S. (1977). Investment Performance of Common Stocks in Relation to their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. *The Journal of Finance, 32, 3,* 663-682.

Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. *Journal of Financial Economics, 12, 1,* 129-156.

Bernard, V.L., & Thomas, J.K. (1989). Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? *Journal of Accounting Research, 27,* 1-36.

Bhandari, L.C. (1988). Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence. *The Journal of Finance, 43, 2,* 507-528.

Brav, A., Geczy, C., & Gompers, P.A. (2000). Is the abnormal return following equity issuances anomalous? *Journal of Financial Economics, 56, 2,* 209-249.

Breeden, D.T. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics, 7, 3,* 265-296.

Box, G.E.P., & Draper, N.R. (1987). *Empirical model-building and response surfaces.* John Wiley & Sons.

Campbell, J.Y., & Cochrane, J.H. (1999). By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. *Journal of Political Economy, 107, 2,* 205-251.

Campbell, J.Y., Hilscher, J., & Szilagyi, J. (2008). In Search of Distress Risk. *The Journal of Finance, 63, 6,* 2899-2939.

Carhart, M.M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance, 52, 1,* 57-82.

Chan, K., Chan, L.K.C., Jegadeesh, N., & Lakonishok, J. (2001). Earnings Quality and Stock Returns. *Journal of Business, 79, 3,* 1041-1082.

Chan, L.K.C., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and Stock Returns in Japan. *The Journal of Finance, 46, 5,* 1739-1764.

Chopra, N., Lakonishok, J., & Ritter, J.R. (1992). Measuring abnormal performance: Do stocks overreact? *Journal of Financial Economics, 31, 2,* 235-268.

Clarke, R.G., Krase, S., & Statman, M. (1994). Tracking Errors, Regret, and Tactical Asset Allocation. *The Journal of Portfolio Management, 20, 3,* 16-24.

Clayman, M.R., Fridson, M.S., & Troughton, G.H. (2012). *Corporate Finance: A Practical Approach.* John Wiley & Sons.

Core, J.E., Holthausen, R.W., & Larcker, D.F. (1999). Corporate governance, chief executive officer compensation, and firm performance. *Journal of Financial Economics, 51, 3,* 371-406.

Dawkins, R. (1976). *The Selfish Gene*. Oxford: Oxford University Press.

DeBondt, W.F.M., & Thaler, R.H. (1985). Does the Stock Market Overreact? *The Journal of Finance, 40, 3,* 793-805.

DeBondt, W.F.M., & Thaler, R.H. (1987). Further Evidence on Investor Overreaction and Stock Market Seasonality. *The Journal of Finance, 42, 3,* 557-581

Eberhart, A.C., Maxwell, W.F., & Siddique, A.R. (2004). An Examination of Long-Term Abnormal Stock Returns and Operating Performance Following R&D Increases. *The Journal of Finance, 59, 2,* 623-650.

Fama, E.F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance, 25, 2,* 383-417.

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

Fama, E.F., & French, K.R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33, 1,* 3-56.

Fama, E.F., & French, K.R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116, 1,* 1-22.

Fama, E.F., & MacBeth, J.D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy, 81, 33,* 607-636.

Fairfield, P.M., & Whisenant, J.S. (2001). Using Fundamental Analysis to Assess Earnings Quality: Evidence from the Center for Financial Research and Analysis. *Journal of Accounting, Auditing & Finance, 16, 4,* 273-295.

George, T.J., & Hwang, C.-Y. (2010). A resolution of the distress risk and leverage puzzles in the cross section of stock returns. *Journal of Financial Economics, 96, 1,* 56-79.

Gibbons, M.R., Ross, S.A. & Shanken, J. (1989). A Test of the Efficiency of a Given Portfolio. *Econometrica, 57, 5,* 1121-1152.

Gompers, P., Ishii, J., & Metrick, A. (2003). Corporate Governance and Equity Prices. *The Quarterly Journal of Economics, 118, 1,* 107-156.

Graham, B., & Dodd, D.L. (1934). *Security Analysis: Principles and Technique*. Mcgraw-Hill Education Ltd.

Grossman, S.J., & Stiglitz, J.E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review, 70, 3,* 393-408.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting Anomalies: An Investment Approach. *The Review of Financial Studies*, *28, 3,* 650-705.

Huberman, G., & Regev, T. (2001). Contagious Speculation and a Cure for Cancer: A Nonevent that Made Stock Prices Soar. *The Journal of Finance, 56, 1,* 387-396.

Ikenberry, D., Lakonishok, J., & Vermaelen, T. (1995). Market underreaction to open market share repurchases. *Journal of Financial Economics*, *39, 2-3,* 181-208.

Jegadeesh, N. (1990). Evidence of Predictable Behavior of Security Returns. *The Journal of Finance, 45, 3,* 881-898.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, *48, 1*, 65-91.

Jegadeesh, N., & Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *The Journal of Finance, 56, 2,* 699-720.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Economerica*, *47, 2*, 263-292.

Lakonishok, J., Shleifer, A., & Vishny, R.W. (1994). Contrarian Investment, Extrapolation, and Risk. *The Journal of Finance, 49, 5,* 1541-1578.

LeRoy, S.F., & Porter, R.D. (1981). The Present-Value Relation: Tests Based on Implied Variance Bounds. *Econometrica, 49, 3,* 555-574.

Lewellen, J. (2004). Predicting returns with financial ratios. *Journal of Financial Economics, 74, 2,* 209-235.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics, 47, 1,* 13-37.

Lo, A.W., & MacKinlay, C. (1988). Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test. *The Review of Financial Studies, 1, 1,* 41-66.

Lo, A.W. (2004). The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective. *Journal of Portfolio Management, 30,* 15-29.

Loughran, T., & Ritter, J.R. (1995). The New Issues Puzzle. *The Journal of Finance, 50, 1,* 23-51.

Loughran, T., & Vijh, A.M. (1997). Do Long-Term Shareholders Benefit From Corporate Acquisitions? *The Journal of Finance, 52, 5,* 1765-1790.

Lucas, R.E. (1978). Asset Prices in an Exchange Economy. *Econometrica, 46, 6,* 1429-1445.

Malkiel, B.G. (1973). *A Random Walk Down Wall Street.* W. W. Norton & Company, Inc.

Malkiel, B.G. (2003). The Efficient Market Hypothesis and Its Critics. *The Journal of Economic Perspectives, 17, 1,* 59-82.

Martani, D., & Khairurizka, R. (2009). The effect of financial ratios, firm size, and cash flow from operating activities in the interim report to the stock return. *Chinese Business Review, 8, 6,* 44-55.

McLean, R.D., & Pontiff, J. (2016). Does Academic Research Destroy Stock Return Predictability? *The Journal of Finance, 71, 1,* 5-32.

Nissim, D., & Ziv, A. (2001). Dividend Changes and Future Profitability. *The Journal of Finance, 56, 6,* 2111-2133.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics, 108, 1,* 1-28.

Ohlson, J.A., (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research, 18, 1,* 109-131.

Ou, J.A., & Penman, S.H. (1989). Accounting Measurement, Price-Earnings Ratio, and the Information Content of Security Prices. *Journal of Accounting Research, 27,* 111-144.

Pástor, L., & Stambaugh, R.F. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy, 111, 3,* 642-685.

Penman, S.H., Richardson, S.A., & Tuna, I. (2007). The Book-to-Price Effect in Stock Returns: Accounting for Leverage. *Journal of Accounting Research, 45, 2,* 427-467.

Perold, A.F. (1988). The implementation shortfall: Paper versus reality. *The Journal of Portfolio Management, 14, 3,* 4-9.

Roberts, H. (1967). Statistical versus Clinical Prediction of the Stock Market. *Unpublished manuscript, Center for Research in Security Prices, University of Chicago.*

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management, 11, 3,* 9-16.

Samuelson, P.A. (1947). *Foundations of Economics Analysis.* Cambridge, MA: Harvard University Press.

Samuelson, P.A. (1965). Proof that properly anticipated prices fluctuate randomly. *Chapter 2 in The World Scientific Handbook of Futures Markets,* 25-38.

Sharpe, W.F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance, 19, 3,* 425-442.

Shiller, R.J. (1981). The Use of Volatility Measures in Assessing Market Efficiency. *The Journal of Finance, 36, 2,* 291-304.

Shin, H.H., & Soenen, L. (1998). Efficiency of Working Capital and Corporate Profitability. *Financial Practice and Education, 8, 2,* 37–45.

Siegel, J. J., & Coxe, D. G. (2002). *Stocks for the long run* (Vol. 3). New York: McGraw-Hill.

Simon, H.A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics, 69, 1,* 99-118.

Sloan, R.G. (1996). Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? *The Accounting Review, 71, 3,* 289-315.

Stattman, D. (1980). Book values and expected stock returns. *The Chicago MBA: A journal of selected papers, 4, 1,* 25-45.

Zarowin, P. (1990). Size, Seasonality, and Stock Market Overreaction. *Journal of Financial and Quantitative Analysis, 25, 1,* 113-125.

Appendix A
Indicator Measure Definitions

This section provides details on the construction of each variable used for ranking, sorting and cross-sectional regressions. All definitions are based on established and well-known papers from notable researchers. While the calculation of performance measures follows Novy-Marx (2013) and Asness et. al. (2014), the calculation of inexpensiveness measures follows Fama and French (1993).

Before starting with the variable definitions, we want to rehearse the setup of our categories and groups in which the individual measures are arranged. We have two general categories: the inexpensiveness category, where valuation metrics are assigned to, and the performance category, to which all kinds of performance measures belong. While the inexpensiveness category does not have any further groupings below, the performance group is differentiated at two levels. First, we divide between the profitability group and the supplementary group. We chose these two groupings as profitability by itself places a similar importance as the inexpensiveness category. The profitability group is thus final, whereas the supplementary group can be divided in the three sub-groups efficiency, financial stability and growth.

We first define some calculation variables used in the next paragraph. The capital letters either refer to the COMPUSTAT variables or to previously self-defined variables as follows. We define operating cost (OC) as cost of goods sold plus selling, general and administrative expenses (COGS + XSGA), operating income (OI) as EBIT (EBIT) or, if missing, EBITDA minus depreciation and amortization (EBITDA – DP) or. if missing, revenues minus operating cost minus depreciation and amortization (REVT – OC – DP), debt (D) as debt in current liabilities and long-term debt (DLC + DLTT), free cash flow (FCF) as net income plus depreciation minus change in working capital minus capital expenditures (NI + DP – WCAPCH – CAPX), shareholder’s equity (SE) as shareholder’s equity (SEQ) or, if missing, common equity plus the carrying value of preferred stock (CEQ + PSTK) or, if missing, assets minus liabilities (AT – LT), preferred stock (PS) as the redemption value of preferred stock (PSTKRV) or, if missing, the liquidation value of preferred stock (PSTKL) or, if missing, the carrying value of preferred stock (PSTK), deferred taxes (DT) as deferred taxes and investment tax credit (TXDITC) or, if missing, deferred taxes plus investment tax credit (TXDB + ITCB), book equity (BE) as shareholder’s equity plus deferred taxes minus preferred stock (SE + DT – PS), capital employed (CE) as book equity plus debt (BE + D) and lastly, working capital as current assets minus current liabilities (ACT – LCT).

Turning to the actual indicator definitions, we will start within the performance category with the group profitability. For profitability, we calculated gross profits-to-assets (gpa) as revenues minus cost of goods sold (REVT – COGS) scaled by assets (AT), return on capital employed (roce) as operating income (OI) scaled by capital employed (CE), return on equity (roe) as income before extraordinary items (IB) scaled by book equity (BE), EBITDA margin (oidmargin) as EBITDA (EBITDA or REVT – OC) divided by sales (REVT), gross profit margin (gpmargin) as gross profits (REVT – COGS) divided by sales (REVT), free cash flow-to-assets (fcfa) as free cash flow (FCF) scaled by assets (AT) and free cash flow-to-capital employed (fcfce) as free cash flow (FCF) scaled by capital employed (CE). Continuing with the supplementary group, for the sub-group efficiency we have the asset turnover (ato) as sales (REVT) over assets (AT) and working capital turnover as sales (REVT) over working capital (WC). For the sub-group financial stability, we have the equity-to-debt ratio (etd) as book equity (BE) divided by debt (D), the equity-to-assets (eta) ratio as book equity (BE) divided by assets (AT), the current ratio (cr) as current assets (ACT) divided by current liabilities (LCT) and the cash-to-sales ratio (cts) as cash and cash equivalents (CHE) divided by sales (REVT). The last sub-group in the supplementary group is growth for which we have the gross profit growth as gross profits at time t divided by gross profits 36 months ago, each time scaled by assets at the corresponding point in time $(((REVT - COGS)/AT)_t/((REVT - COGS)/AT)_{t-36})$ and the free cash flow growth as free cash flow at time t divided by free cash flow 36 months ago, each time scaled by assets at the corresponding point in time $((FCF/AT)_t/(FCF/AT)_{t-36})$. Finally, the calculation of the inexpensiveness category is based on sorting variables in June that are scaled by market equity from the end of December. We consider three different valuation ratios: the book-to-market ratio as book equity (BE) at t over market equity at t minus 6 months, the earnings-to-price ratio as income before extraordinary items (IB) at t over market equity at t minus 6 months and the free cash flow-to-price ratio as free cash flow (FCF) at t over market equity at t minus 6 months.

Table A1
Persistence of Indicator Measures

This table reports average z-scores for different performance measures. Following Asness et. al. (2014), z-scores $z(x)$ for each indicator measure x are constructed by $z(x) = (r - \mu_r)/\sigma_r$, with r as the vector of ranks $r_i = rank(x_i)$, μ_r as the cross-sectional mean of r and σ_r as the cross-sectional standard deviation of r. Each June, stocks are sorted in ascending order based on their z-scores and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. For each performance measure, we report the time series average of the equally-weighted cross sectional means for the date of portfolio formation (t) and after one year (t + 12 months), five years (t + 60 months) and ten years (t + 120 months), maintaining the initial portfolio assignments. Our sample runs from June 1966 to December 2016 and contains all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6). We only consider performance measures above zero.

Panel A: Profitability Metrics		P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	P10-P1
GP-to-assets	t	-1.56	-1.26	-0.99	-0.69	-0.38	-0.05	0.30	0.66	1.06	1.50	3.06
	t + 12M	-1.37	-1.15	-0.88	-0.61	-0.33	-0.05	0.25	0.57	0.94	1.40	2.77
	t + 60M	-1.08	-1.01	-0.73	-0.51	-0.28	-0.07	0.18	0.45	0.76	1.21	2.29
	t + 120M	-0.96	-0.99	-0.69	-0.45	-0.24	-0.07	0.16	0.40	0.69	1.11	2.07
ROCE	t	-1.49	-1.07	-0.74	-0.44	-0.13	0.18	0.49	0.81	1.15	1.52	3.01
	t + 12M	-0.94	-0.77	-0.60	-0.39	-0.19	0.03	0.29	0.54	0.81	1.20	2.14
	t + 60M	-0.44	-0.43	-0.37	-0.31	-0.18	-0.05	0.09	0.24	0.42	0.70	1.15
	t + 120M	-0.32	-0.32	-0.31	-0.24	-0.17	-0.04	0.07	0.20	0.34	0.55	0.87
ROE	t	-1.49	-1.07	-0.74	-0.43	-0.13	0.17	0.47	0.78	1.10	1.50	3.00
	t + 12M	-0.88	-0.71	-0.55	-0.37	-0.18	0.01	0.22	0.44	0.70	1.08	1.96
	t + 60M	-0.37	-0.39	-0.35	-0.28	-0.18	-0.12	0.01	0.13	0.31	0.54	0.91
	t + 120M	-0.25	-0.28	-0.28	-0.23	-0.17	-0.10	-0.02	0.10	0.22	0.36	0.61
EBITDA margin	t	-1.45	-0.97	-0.58	-0.23	0.10	0.41	0.72	1.02	1.30	1.59	3.04
	t + 12M	-1.18	-0.85	-0.55	-0.28	-0.01	0.26	0.56	0.86	1.19	1.50	2.68
	t + 60M	-0.94	-0.72	-0.51	-0.30	-0.10	0.08	0.34	0.62	0.97	1.33	2.28
	t + 120M	-0.87	-0.65	-0.47	-0.30	-0.14	0.04	0.26	0.51	0.83	1.22	2.09
GP margin	t	-1.55	-1.20	-0.89	-0.59	-0.29	0.01	0.32	0.65	1.02	1.47	3.02
	t + 12M	-1.39	-1.11	-0.84	-0.58	-0.31	-0.05	0.24	0.56	0.92	1.37	2.76
	t + 60M	-1.18	-1.02	-0.78	-0.56	-0.35	-0.14	0.09	0.38	0.73	1.16	2.34
	t + 120M	-1.09	-0.98	-0.76	-0.57	-0.40	-0.23	-0.01	0.23	0.56	0.99	2.09
FCF-to-assets	t	-1.56	-1.21	-0.89	-0.57	-0.26	0.07	0.39	0.72	1.07	1.49	3.04
	t + 12M	-0.59	-0.54	-0.45	-0.34	-0.20	-0.05	0.15	0.35	0.58	0.88	1.47
	t + 60M	-0.29	-0.31	-0.27	-0.23	-0.13	-0.05	0.05	0.20	0.30	0.52	0.81
	t + 120M	-0.23	-0.22	-0.20	-0.18	-0.10	-0.04	0.02	0.09	0.23	0.41	0.64
FCF-to-CE	t	-1.56	-1.22	-0.90	-0.58	-0.25	0.07	0.39	0.72	1.07	1.49	3.05
	t + 12M	-0.59	-0.55	-0.47	-0.36	-0.20	-0.05	0.13	0.33	0.57	0.90	1.49
	t + 60M	-0.30	-0.31	-0.28	-0.24	-0.14	-0.05	0.03	0.18	0.29	0.52	0.82
	t + 120M	-0.23	-0.24	-0.22	-0.17	-0.10	-0.05	0.01	0.10	0.21	0.40	0.63

Panel B: Supplement. Metrics		P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	P10-P1
Asset turnover	t	-1.50	-1.12	-0.82	-0.52	-0.23	0.07	0.38	0.72	1.09	1.51	3.01
	t + 12M	-1.41	-1.03	-0.71	-0.42	-0.16	0.10	0.36	0.66	0.99	1.42	2.83
	t + 60M	-1.19	-0.85	-0.52	-0.27	-0.05	0.15	0.36	0.57	0.84	1.29	2.48
	t + 120M	-1.04	-0.70	-0.39	-0.16	0.03	0.21	0.38	0.56	0.80	1.22	2.26
WC turnover	t	-1.33	-0.74	-0.40	-0.10	0.19	0.47	0.76	1.03	1.31	1.59	2.92
	t + 12M	-1.10	-0.59	-0.30	-0.05	0.18	0.43	0.68	0.90	1.14	1.36	2.46
	t + 60M	-0.77	-0.38	-0.18	0.01	0.19	0.38	0.58	0.76	0.95	1.15	1.92
	t + 120M	-0.58	-0.23	-0.04	0.10	0.23	0.41	0.56	0.73	0.87	1.07	1.66
Equity-to-debt	t	-1.53	-1.19	-0.92	-0.66	-0.40	-0.15	0.12	0.41	0.77	1.35	2.88
	t + 12M	-1.36	-1.06	-0.83	-0.61	-0.39	-0.17	0.06	0.30	0.63	1.15	2.51
	t + 60M	-0.95	-0.80	-0.66	-0.51	-0.35	-0.20	-0.04	0.14	0.38	0.79	1.74
	t + 120M	-0.74	-0.66	-0.57	-0.48	-0.35	-0.24	-0.09	0.04	0.25	0.60	1.34
Equity-to-assets	t	-1.53	-1.19	-0.91	-0.64	-0.37	-0.11	0.16	0.46	0.81	1.37	2.90
	t + 12M	-1.35	-1.07	-0.83	-0.59	-0.35	-0.13	0.10	0.33	0.66	1.16	2.52
	t + 60M	-0.93	-0.81	-0.64	-0.48	-0.32	-0.16	-0.01	0.16	0.39	0.79	1.72
	t + 120M	-0.72	-0.64	-0.53	-0.41	-0.31	-0.18	-0.07	0.06	0.26	0.61	1.32
Current ratio	t	-1.57	-1.27	-0.97	-0.66	-0.37	-0.09	0.20	0.50	0.84	1.38	2.95
	t + 12M	-1.36	-1.09	-0.82	-0.54	-0.30	-0.08	0.14	0.37	0.64	1.08	2.44
	t + 60M	-1.13	-0.90	-0.63	-0.41	-0.22	-0.07	0.09	0.26	0.43	0.74	1.87
	t + 120M	-1.03	-0.84	-0.56	-0.38	-0.23	-0.07	0.06	0.20	0.33	0.61	1.64
Cash-to-sales	t	-1.55	-1.23	-0.95	-0.68	-0.41	-0.13	0.15	0.45	0.79	1.35	2.90
	t + 12M	-1.19	-0.96	-0.80	-0.60	-0.42	-0.22	-0.01	0.23	0.53	1.11	2.30
	t + 60M	-0.90	-0.76	-0.64	-0.51	-0.40	-0.27	-0.15	0.02	0.25	0.77	1.67
	t + 120M	-0.78	-0.68	-0.60	-0.53	-0.42	-0.33	-0.24	-0.10	0.09	0.56	1.34
GP growth	t	-1.50	-1.10	-0.78	-0.48	-0.19	0.09	0.38	0.68	1.01	1.46	2.96
	t + 12M	-0.74	-0.50	-0.35	-0.21	-0.09	0.01	0.14	0.27	0.46	0.73	1.48
	t + 60M	0.19	0.04	0.00	-0.02	-0.04	-0.07	-0.07	-0.08	-0.09	-0.07	-0.26
	t + 120M	0.03	-0.01	-0.03	-0.05	-0.04	-0.04	-0.04	-0.04	-0.05	-0.02	-0.05
FCF growth	t	-1.51	-1.12	-0.77	-0.43	-0.12	0.18	0.48	0.79	1.14	1.52	3.04
	t + 12M	-0.22	-0.23	-0.17	-0.10	-0.05	0.05	0.11	0.16	0.23	0.29	0.51
	t + 60M	0.06	0.07	0.04	0.04	-0.02	-0.04	-0.03	-0.03	0.01	0.00	-0.05
	t + 120M	0.05	0.06	0.04	0.04	0.02	-0.01	-0.01	0.03	0.04	0.01	-0.04

Table A2
Alphas and Factor Loadings

This table reports annualized average excess returns, abnormal returns and factor loadings for different risk factors and the multivariate strategy proposed in Table V, which showed monthly excess returns and abnormal returns without factor loadings. The strategy is set up as follows: In each June, stocks are sorted in ascending order based on their composite z-score and subsequently assigned to a decile portfolio constructed with NYSE breakpoints. We then calculate equally weighted returns for each decile portfolio for every of the subsequent 12 months, starting in July of the same year and ending in June of the following year. We now show the time series average of the monthly excess returns, standard deviation and abnormal returns relative to the CAPM, Fama-French three-factor and five-factor models. For the latter asset pricing models, we also show factor loadings. As an additional measure, we show results relative to a monthly momentum factor MOM, which is sourced from Kenneth French's data library. Our sample runs from July 1966 to December 2016 and contains all US common stocks (CRSP shrcd equal to 10 or 11) excluding financial firms (one-digit SIC codes equal to 6). We only consider performance measures above zero. Significance levels for the Value Investing Strategy are shown by *** p<0.01, ** p<0.05 and * p<0.01.

	Rm-Rf (market)	SMB	HML	RMW	CMA	MOM	Value Investing Strategy
Mean	6.26	2.93	4.47	3.12	4.04	7.85	16.18***
1-factor model							
Alpha	0.00	1.77	5.55	3.86	5.16	8.73	17.36***
Beta (market)	1.00	0.19	-0.17	-0.12	-0.18	-0.13	-0.17***
3-factor model							
Alpha	0.00	0.00	0.00	4.21	2.60	10.95	14.10***
Beta (market)	1.00	0.00	0.00	-0.07	-0.10	-0.20	-0.17***
Beta (SMB)	0.00	1.00	0.00	-0.23	0.01	-0.01	0.38***
Beta (HML)	0.00	0.00	1.00	0.01	0.45	-0.37	0.40***
5-factor model							
Alpha	0.00	0.00	0.00	0.00	0.00	8.56	12.39***
Beta (market)	1.00	0.00	0.00	0.00	0.00	-0.13	-0.14***
Beta (SMB)	0.00	1.00	0.00	0.00	0.00	0.04	0.44***
Beta (HML)	0.00	0.00	1.00	0.00	0.00	-0.58	0.33***
Beta (RMW)	0.00	0.00	0.00	1.00	0.00	0.25	0.28***
Beta (CMA)	0.00	0.00	0.00	0.00	1.00	0.45	0.14*