SCREENING FOR STOCK-CHARACTERISTICS AND CONTINUATION OF THE DUAL MOMENTUM APPROACH

by

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A thesis submitted to the faculty of
the University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Master of Science in
Economics

Charlotte

2016

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ABSTRACT

KONSTANTIN EKSTROM. Screening for stock-characteristics and continuation of the dual momentum approach. (Under the direction of DR. CRAIG A. DEPKEN II)

The momentum strategy suggests buying stocks that have appreciated the most and selling those that have depreciated the most. The strategy is well documented and has shown persistence over the years. A problem most trading strategies face is that profits attenuate, or even vanish, as they become more widely known. The profits from the momentum strategy have clearly attenuated since Carhart presented his paper in 1997, where he showed that momentum had significant explanatory power of future returns. Attenuation requires finding ways to modify the momentum strategy in order to elevate the profits. This paper looks into two potential techniques. One focuses on identifying stock characteristics associated with high momentum returns. Elevation would then be achievable by screening the universe of stocks for these characteristics before applying the momentum strategy. Another technique, dual momentum, only allows a stock to enter the portfolio if it both exhibits relatively high momentum and has momentum higher than that of a certain benchmark. Of the characteristics considered only gross profitability exhibited consistent higher marginal momentum returns but following a strategy that screens for this characteristic does not improve the performance. Recent research has documented idiosyncratic risk as a common explanatory variable of high and significant momentum returns. Consistent higher marginal returns could not be shown for this characteristic. The dual momentum approach did not improve the performance. The conclusion is that momentum may be explained by a herding behavior that results in investors ignoring fundamentals.

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

1.1 Momentum and Source of Profits

A widely known trading strategy is momentum, which was formally presented by Jegadeesh and Titman (1993). They showed that profits could be made through strategies that involved buying past winners and selling past losers with a holding period of 3-12 months. More specifically, they set up a strategy where they first calculated the momentum statistic that was defined as the 12-month total return ignoring the very last month in order to avoid short term reversal. This was denoted as 12-month-1-month momentum and can intuitivly be thought of as total percentage return over 11 months but lagged one month. They then ranked the stocks based on the 12-month-1-month momentum variable, and then took a long position in the upper quintile and a short position in the lower quintile. Profits were realized because stocks that are heading in one direction, up or down, tend to continue over a substantial period.

The momentum strategy reached the broader audience when Carhart (1997) showed that adding the momentum variable as a regressor in a Fama-French 3-factor model significantly increased the model's explanatory power of expected returns (Hamish, Edwards, and J. Lazzara, 2015). The momentum variable Carhart (1997) used was the 12-month-1-month momentum statistic directly taken from the work of Jegadeesh and Titman (1993).

The purpuse of numerous papers has been to understand why the strategy works or rather finding the common source of the momentum profits. One of the most recent contributions is done by Bandarchuk and Hilscher (2013) who conducted a more extensive analysis of this question. Their starting point was that there is no widely accepted explanation for high and significant momentum returns. They began by identifying two kinds of explanations that were common in the literature. The first focuses on behavioral explanations such as herding behavior among investors, paying too much attention to recent performance, and/or underreacting to new information. The latter was an explanation proposed by Jegadeesh and Titman (1993). The other part focuses on identifying certain stock characteristics since double sorting in a screening process on stock-characteristics has proven to enhance returns. Among these were small cap stocks with low analyst coverage, high analyst forecast dispersion, low return R^2, and high book-to-market ratio. However, they concluded that these characteristics often served as a proxy for uncertainty and thereby rather supported the behavioral explanations.

Arena, Haggard, and Xuemin (2008) suggested idiosyncratic risk or idiosyncratic volatility (ivol) as a common source of momentum profits. ivol was defined by the regression:

$$r_{i,t} = \alpha_i + \beta_{1,i} r_{m,t} + \beta_{2,i} r_{m,t-1} + \epsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is return of stock i at time t, and $r_{m,t}$ is the return of market at time t. The standard deviation of $\epsilon_{i,t}$, over the past 12 months, was then defined as ivol for the respective stock. The reason for including the lagged market return was to account for possible non-synchronus trading. They could then conclude that momentum returns were higher among stocks with higher ivol.

Bandarchuk and Hilscher (2013) used this insight when conducting a more comprehensive analysis of stock characteristics and momentum. Their findings indicated that the common factor, among all previously documented characteristics that had proven to co-vary with momentum profits, was extreme past returns. When running regressions of the characteristics controlling for ivol the significance of all others vanished. This indicated that screening for stock chararacteristics such as book-to-market, market equity, and other prevously documented variables would not elevate the realized returns when following the momentum strategy.

1.2 Attenuating Persistence

The momentum strategy is still profitable but Hamish et al. (2015) presented evidence that the momentum strategy has attenuated since 1997 when Carhart presented his findings. They support their statement by showing that returns have decreased and at the same time volatility and downside risk have increased. There was a clear break in these variables around 1997.

Attenuation of a strategy does not nessecarily mean that the profits eventually will completely vanish. Asness (2015) argues that it is possible to measure persistence of strategy by looking at stability of value spread, i.e. difference between long and short portfolio, and volatility. Hamish et al. (2015) argue in the same spirit by referring to a paper by Leote de Carvalho, Xiao, and Moulin (2011) where they concluded that the highest sharpe ratios, i.e the return that exceeds the risk-free interest rate divided by volatility, were found among minimum-variance portfolios despite the fact that Haugen and Heins (1975) presented evidence of superiority of low volatility stocks over high volatility many years earlier. This implies that there are strategies for which profitability persists, even after they have become widely known. Arena et al. (2008) argues that lack of opportunity to arbitrage away high Ivol risk, compared to low Ivol stocks, serves as a possible explanation for why momentum profits have persisted over the years.

1.3 Suggested Improvements

This section aims to give the reader an overviw of suggested improvements to the momentum strategy. The latest improvements involve either screening for stock characteristics or using past equity prices.

1.3.1 Stock-Characteristics

Much of the literature has focused on identifying certain characteristics that covariate with momentum returns. Screening for these should then result in elevated momentum returns. Some of the suggested characteristics are low market equity, low analyst coverage

(Hong, Lim, and Stein, 2000), high analyst forecast dispersion (Zhang, 2006), low return R^2 (Kewei, Wei, and Lin, 2006), low book-to-market ratios (Daniel and Titman, 1999), high-risk credit rating (Avramov, Chordia, and Philipov, 2007), and high turnover (Lee and Swaminathan, 2007). Regarding book-to-market, the return difference between top and bottom quintile was largest at low ratios but overall highest return figures were found when both the momentum variable and the book-to-market ratio were high. However, Bandarchuk and Hilscher (2013) support the fact that screening for stock-characteristics elevates momentum profits but that the correlation suffers from omitted variable bias, which could be connected to idiosyncratic risk.

Other recent approaches have focused on creating portfolios where pure-play portfolios are constructed. This means that separate portfolios following each strategy are combined to create one portfolio, rather than using a screening process. Asness, Moskowitz, and Pedersen (2013) showed a strategy that selects the highest value stocks, defined as the book-to-market ratio, is negatively correlated with a strategy that selects stocks with highest momentum and that gains could be made from pure-play combinations of the two strategies. This was proven across markets and asset classes. One reason for the observed correlation, they argued, was the fact that momentum was driven by a herding behavior while value represented the contrarian view. For US equities, they used common equity listed at CRSP from 1972 to 2011. The selection process consisted of three steps: (1) rank all stocks in ascending order based on value and 12-month-1-month momentum, separately; (2) Divide the stocks based on their ranks into three portfolios, tertiles, and take a long position in the portfolio consisting of top terile, and take a short position in the bottom terile. Doing this for momentum and value separately results in two hedge portfolios; (3) Create a portfolio that assigns equal weights to the value hedge portfolio and momentum hedge portfolio. The final portfolio was then rebalanced at the beginning of each month following the same selection process.

For 50/50 excess return portfolios, consisting of equity, the Sharpe ratio increased by about 50 percent and the volatility decreased by half. This proved that information about stock-level characteristics and momentum served as complements. Intuitively it may be accurate to make an analogy to the framework of Markowitz (1952) mean-variance allocation. In this case each strategy, value and momentum, forms a portfolio that can be viewed as one asset. According to Markowitz (1952), it becomes possible to form a portfolio of two assets with lower variance and higher Sharpe ratio than holding each individually. Since the two strategies can be said to form two individual assets, which are negatively correlated, a new portfolio of the two can be formed that has lower variance and hence higher Sharpe ratio as in this case.

Fisher, Shah, and Titman (2015) can be viewed as a continuation of the approach introduced by Asness et al. (2013), which they further developed. Fisher et al. (2015) used stocks listed at Center for Security Research (CRSP) from year 1975 to 2013 and the method for selecting stocks can be summarized as follows: (1) Define value as the book-to-market ratio and momentum as 12-month-1-month return; (2) Rank the stocks in ascending order according to value and momentum separately and assign the capitalization value to each respective stock; (3) Choose which stock to include by assigning those having an aggregated capitalization, i.e. capitalization values added from the bottom of the ranking list through the stock in interest, above chosen break point; (4) Weight each stock in the portfolio based on its capitalization value. They ran three models using this approach. In the first model they made value and momentum portfolios separately and the assigned those equal values in the final. In the second model, a stock only entered the portfolio if it satisfied a certain rank break point for both the rank of value and the rank of momentum. The third involved a home-made scoring system that did not improve the second model.

For the 50/50 portfolios they obtained similar results to Asness (2015) even though the method differed slightly. For the second strategy, where each stock had to have a momentum rank above 50 percent and value rank above 90 percent, the Sharpe ratio improved 10 percent. However, they also showed that a pure-play portfolio of 70/30 value and momentum, respectively, could generate about the same improvement. The main advantage of the second model was the dramatically decreased turnover but because of low transaction costs, they concluded that it only affects the performance minimally.

1.3.2 Past Equity Prices

The use of past equity prices to elevate momentum profits is what the most recent liteature suggests. Arena et al. (2008) showed that idiosyncratic volatility exhibited major covariation with momentum returns even after controlling for stock-characteristics.

Bandarchuk and Hilscher (2013) further examined the relation and presented evidence that the idiosyncratic risk served as a common factor for previosly documented stock-characteristics that showed covariation with momentum profits. They concluded from this that screening for stock-characteristics would not elevate the momentum returns.

Another recent extension, with a similar starting point, using past equity prices, is the work by Daniel and Moskowitz (2014) who seeked to overcome the crash risk, i.e a major decrease in the portfolio value duing a short period, by choosing stocks based upon forecasted volatility and return in a dynamic setting simulating the strategy from year 1927 to 2011. First, they forecasted returns one month ahead running a regression with past volatility and a bear market indicator, which is a dummy that equals 1 if culmulative return over the past 24 months of the CRSP value-weighted index is negative. Based on the forecasted returns an hedge portfolio could be created taking long positions in the top declie and short positions in bottom decile. Using the GJR-GARCH technique to forecast volatility they were able to find optimal weights by using the Lagrange technique in order to maximize the return of portfolio with respect to forecasted volatility. This approach doubled the Sharpe ratio and cut maximum drawdown by half, compared to regular momentum. Besides this, one main insight was that returns of momentum investing are negatively skewed.

Han, Zhou, and Zhu (2015) devised a simpler technique: a stop-loss strategy to avoid crash risk using stock data listed at CRSP from year 1926 to 2013. The strategy was to divest stocks that had decreased 10 percent or more since the beginning of the month when the portfolio had been rebalanced. Short positions were covered as soon as the price increased 10 percent or more. This strategy doubled the average return and sharp-ratios. Months with the highest drawdowns for equal-weighted portfolios went from -49.79 percent to -11.36 percent, and value-weighted from -64.97 percent to -23.28 percent.

Jacobs, Regele, and Weber (2015) picked up the insight about distribution of returns and took it into account when selecting stocks to enter the portfolio. The main idea behind their method is to take advantage of negatively skewed return distributions. They test the hypothesis that momentum gains and negative skewness of returns are strongly correlated, a phenomenon that was shown by Daniel and Moskowitz (2014) and Barroso and Santa-Clara (2015). The method used by Jacobs et al. (2015) for selecting stocks can be summarized in four steps.

1. Calculate skewness of each stock using the total skew measure as gathered from Bali, Brown, Murray, and Tang (2015).

$$TotalSkew_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D} \left[\frac{r_{i,d} - \mu_i}{\sigma_i} \right]^3 \tag{2}$$

   Here, $TotalSkew_{i,t}$ is systematic and idiosyncratic skewness combined for stock i, in a given year t. D_t is number of trading days in year t. $r_{i,d}$ is return for stock i, on trading day d. μ_i is mean return of stock i. σ_i is standard deviation for stock i.

2. Rank all stocks based on this measure in ascending order and divide into quintiles.

3. Calculate time-series momentum using the 12-months-1-month rule and rank the stocks in ascending order, based on this variable, and divide into quintiles.

4. Take long positions stocks that belong to highest quintile based on both skewness and momentum and take short positions in stocks that fall under the lowest quintile based on skewness and within that quintile use the lowest momentum quintile.

The portfolio is then evaluated once a month and stocks that do not fulfill the criteria are divested and replaced. This approach increased Sharpe ratio by 50 percent and maximum downturn became 60 percent lower. This means that both techniques were successful in improving the performance.

An alternative method called Dual Momentum was introduced by Antonacci (2014) and backtested using data from 1974 to 2011. This strategy combines cross-sectional and time-series momentum such that the stock must exhibit both in order to enter the portfolio. An asset exhibits cross-sectional momentum if it has performed relatively better than others. Time-series momentum is defined as positive excess return, compared to a risk-free investment, over the look-back period. When back testing the strategy, he tested the strategies among four asset classes, which consisted of only two to three investable assets within each category. The selection process then consisted of two steps: for each category, (1) choose the asset that has performed best relative to the others; and (2) let the asset enter the portfolio if it also exhibits time-series momentum, otherwise invest in the risk-free asset until the next portfolio evaluation date. The portfolio was than rebalanced monthly and stocks that did not exhibit both cross-sectional and time-series momentum were divested.

This approach increased the Sharpe ratio by about 50 percent to 0.73 and cut the maximum drawdown to -23.01 percent, less than half for equities. Despite the fact that the backtesting of the equity category only contained two indices and a risk-free asset, the enhanced performace from following the strategy makes it appealing for further tests.

1.4 Research Approach

The discussion above suggests screening for stock-characteristics would not improve the performance of the momentum strategy. Experimenting with past prices should rather be the appropriate approach. Example of this is sorting on idiosyncratic risk. The aim of this paper is to conduct an analysis on the impact of stock characteristics, using an alternative approach. If the analysis confirms that screening for stock-characteristics does not improve performance then that part of the literature can defenitely be ignored when attempting an elevation of momentum returns. Since the most recent research suggests idiosyncratic risk is a common source of momentum returns, the same approach used for stock-characteristics will be used for testing whether the insight can be useful for trading purposes.

The dual momentum framework was presented as a simple approach that offers major improvment and this is why it is appealing to look into further. The second part of this paper therefore aims to apply the framwork of dual momentum to a larger universe of stocks since the backtesting procedure in the original paper only contained a limited amount of data when applied to equity, two indices and a risk-free asset.

The intuition behind dual momentum can be summarized as only investing in a portfolio of stocks if it can be viewed as favorable compared to taking a position in the benchmark. Therefore a modified version will be developed and backtested, named risk-adjusted momentum. Here, the variable for comparison is a risk-adjusted return measure, which is the return divided by volatility.

Since there is a break documented in the performance of the momentum strategy around 1997 it becomes adequate to compare the period before and after along with the whole sample period. Doing this also enables telling whether the suggested improvments manage to restore the performance, make it perform even better than perviously, only offer minor improvment or not improve at all.

CHAPTER 2: EMPIRICAL APPLICATION

2.1 Data

Data used in the analysis are monthly equity prices from July 1963 to December 2013, obtained from Center for Research in Security Prices (CRSP). Accounting data for each stock was gathered from Compustat. The very same data were used in Dickson (2015) and contains: common equity securities (Share codes 10 and 11) of all firms listed on NYSE, NASDAQ and AMEX (exchange codes 1, 2 and 3 respectively). Stock-characteristics considered are size ($log[ME]$), value ($log[BE/ME]$), gross profitability (GP) and investments (INV).[1] Size is measured as natural logarithm of total market equity of shares outstanding. Value is measured as the natural logarithm of book value of equity divided by market value of equity. Book equity is calculated as shareholder equity subtracted by preferred stock plus deffered taxes, when available. Calculation of shareholder equity is consistent with what Fama and French (1993) used to define HML. In Compustat, shareholder equity is dedined as SEQ. If that was not available common equity plus carrying value of preferred stock (CEQ+PSTX) was used, and in special cases total assets subtracted by total liabilities (AT-LT). Deferred taxes and tax credits were defined in compustat as TXDITC or if not available TXDB and ITCB were used, which are the two separately reported. Preferred stock was redemption value (PSTKR), liquidating value (PSTKRL) or carrying value (PSTK) depending on what was available. Gross profitability is defined as gross return divided by assets. In Compustat gross profits and extraordinary items (GP and IB) were used, divided by total assets. Gross profits could alternatively be defined as total revenue (REVT) minus

[1]When refering to size/market equity and value/book-to-market in the proceeding of this paper it is the log versions considered.

cost of goods sold (COGS). Investments is measured as book value of assets in period t divided by the book value of assets in period t-1. This approach follows Fama and French (2015) By taking the natual logharithm of market equity and the book-to-market ratio make the distribution more symmetric, which reduces the impact of outliers. Monthly market excess returns and risk-free rates are gathered form Kenneth French's website.[2] These two variables are then added together to calculate the market return.

Size is generally interpreted as a proxy for information uncertainty. That is, investors tend to be more updated about larger companies leading to a lagged reaction to news about smaller stocks (Bandarchuk and Hilscher, 2013). That means momentum is expected to be higer among smaller companies. Hence, a negative correlation between size and momentum is expected. Also the value characteristic can be viewed as a proxy for uncertainty since the ratio reflects expectations of future profits, which leads to closer monitoring (Bandarchuk and Hilscher, 2013). In this case, a positive relation is expected with momentum. Gross profitability is an untraditional characteristic to look at within this context and can be viewed in the same way as value, which means that we can expect higher momnetum retuns the higher the gross profitability (Novy-Marx, 2013). Investments is also an untraditional characteristic to look at. If investments are interpreted as higher anticipated returns by the company then a positive relationship is expected. On the other hand if it is interpreted as less cash flow, and a lower dividend payout now, then a negative relationship is expected.

Consistent with Novy-Marx (2013) the top and bottom 1 percent of stocks are excluded in order to decreace the impact of outliers. All accounting variables need to be rearragned such that the information reflects what was known at the decision date. This enables calculation of an actual return earned from making an investment decision at each evaluation date. Consistent with Fama and French (1992) monthly sock returns for July year t to June year t+1 are matched with accounting variables gathered from Compustat for fiscal years ending in calendar t-1.

[2]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

2.2 Portfolio Construction

2.2.1 Stock-Level Characteristics

The method can be described as a double sorting process where the stocks first are sorted on respective factor loadings, which is described below, then on the 12-month-1-month momentum measure.

To enable examination of marginal return by holing a portfolio more dominant in a certain characteristic, portfolios need to be constructed such that the only difference is the characteristic in interest. A way to achieve this is by following a process of three steps: first (1) regress the characteristic that is desired to vary across the portfolios on all characteristics. Second (2), save the residuals and rank the stocks in descending order based on their respective residual. Third (3), divide the stocks into a portfolios based on rank break points. In this paper, the stocks are divided into five portfolios. Equation 3 gives a formal explanation of the procedure, which follows the approach proposed by Kirby and Cordis (2015):

$$x_{i,j,t} = \alpha + \sum_{i=1,j\neq 1}^{k} \beta_i x_{i,j,t} + e_{i,j,t} \tag{3}$$

In equation 3, $x_{i,j,t}$ is value of characteristic j, attributed to equity i in time t. The least square regression is repeated $\forall t$. The residuals $e_{i,j,t}$ for each $j \in (1, \ldots, k)$ are stored, and then used to rank the stocks before dividing them into five portfolios. The next step is to apply the momentum strategy to each of these five portfolios. This is achieved by first ranking the stocks in descending order based on their 12-month-1-month momentum measure and then divide them into five portfolios. This implies that a total of 25 portfolios, representing four percent of the stock universe, will be backtested for each characteristic; in total 100 portfolios. This selection process is then repeated monthly when rebalancing the portfolios. Because of the evidenced break around 1997 the periods considered are: the full sample period 1963-2013; until the strategy can be considered as widely known

1963-1997; and after, 1998-2013.

A statistical measure needs to be employed in order to determine whether the difference in performance between constructed portfolios are significant. This can be achieved by employing a simple t-test of differences in means. This method is outlined in the equation below:

$$t = \frac{\bar{x}_{High} - \bar{x}_{Low}}{\sqrt{\frac{S_{High}}{\#ofMonths} + \frac{S_{Low}}{\#ofMonths}}} \tag{4}$$

Here, $\bar{x}_{High}$ is average monthly profit of quintile 1 and $\bar{x}_{Low}$ is the corresponding for quintile 5. S_{High} and S_{Low} is the standard deviation of monthly profit for quintile 1 and 5 respectivly. The t-stat is then compared to a critical value corresponding to 95 percent confidence. If the null of no relationship is rejected then the conclusion can be drawn that stocks exhibiting dominance in a certain characteristic are expected to have higher momentum return, in those cases where the relation is expected to be positive.

The t-statistics were calculated using equation 4 such that all high minus low (quintile 1-quintile 5) combinations for momentum were considered. For example, BEME quintile 1 in panel A was calculated using $\bar{x}_{High}$ equal to BEME=1/Mom=1 in table 5 and $\bar{x}_{Low}$ equal to BEME=5/Mom=1 in the same table. The t-stat for BEME quintile 2 was calculated using $\bar{x}_{High}$ equal to BEME=1/Mom=2, $\bar{x}_{Low}$ equal to BEME=5/Mom=2 etc. By doing this, it becomes posible to say whether the double sorting procedure has any significant impact on the returns.

2.2.2 Idiosyncratic Volatility

Following Arena et al. (2008) an additional characteristic, idiosyncratisk risk or idiosyncratic volatility (ivol), can be calculated from the regression below as the standard deviation of the residuals ϵ_t over the past 12 months:

$$r_{i,t} = \alpha_i + \beta r_{m,t} + \epsilon_{i,t} \tag{5}$$

In equation 5, $r_{i,t}$ is return of stock i in time t, and $R_{m,t}$ is the return on the market portfolio at time t. Arena et al. (2008) also used one lag of the market portfolio but concluded that the differences were very small. Once ivol is calculated for each stock and period they can be treated as another stock-characteristic, which means that the same procedure for backtesting and comparison of portfolios can be used as described in the previous section.

2.2.3 Traditional Momentum

For comparison purposes, portfolios based on the 12-month-1-month rule will be backtested, as this is the common measure of momentum [see e.g. Carhart (1997), Novy-Marx (2013), and Fama and French (2015)].

The backtesting process can be summarized as follows: (1) Rank all stocks in ascending order based on their 12-month-1-month return and select those above a chosen break point. In this paper, the stocks will be divided into 5 portfolios, quintiles, for each of the three periods considered, which are 1965-2013, 1965-1997, and 1998-2013. The reason for excluding the years 1963 and 1964 is to enable comparison purposes since the first two years are consumed when backtesting the dual momentum strategy.

2.2.4 Dual Momentum

The dual momentum strategy presented by Antonacci (2014) has to be modified in order to be applicable to a larger universe of stocks but the procedure of selecting and divesting will remain the same. Here, the method used for backtesting dual momentum will be explained.

Relative strength or cross-sectional momentum is defined as how much one stock has appreciated relative to others but selecting stocks based on this measure is the same as choosing those that have appreciated the most. Absolute momentum or time-series momentum is defined as return that exceeds a benchmark. Due to the long period of low risk-free rates after 2008, the SP500 index will be used as an alternative benchmark. Using a benchmark that is roughly zero would result in the same payoffs as for a regular momentum strategy.

As a benchmark an investable asset is needed but a problem is that SPY ETF, that tracks the SP500 index, has only existed since 1994. This is solved by using the index itself with ticker 'GSPC' as a proxy since the monthly returns should be equal.

The backtesting process can be divided into three steps: (1) Rank each stock based on its 12-month-1-month returns and divide into quintiles; (2) Any stock within the quintile of interest will enter the portfolio if it also exhibits absolute momentum; (3) The portfolio will then be evaluated in the beginning of each month and stocks that are outside the quintile considered or no longer exhibit absolute momentum are divested. If no stocks enter the portfolio, the GSPC will be used as a proxy investment until the next evaluation date. Five portfolios will be considered in this paper for each period looked at, which are 1965-2013, 1965-1997, and 1998-2013. The first two years 1963 and 1964 were consumed in the calculations.

As in the case of screening for stock-characteristics a statistical test needs to be employed in order to decide whether the potential improvments of the dual momentum strategy are significant. The same t-test of differences in mean as described in equation 4 is employed. The equation below shows how the tests are conducted for the difference in performance between traditional and dual momentum:

$$t = \frac{\bar{x}_{DualQuintile} - \bar{x}_{TraditinalQuintile}}{\sqrt{\frac{s_{DualQuintile}}{\#ofMonths} + \frac{s_{TraditionalQuintile}}{\#ofMonths}}}. \tag{6}$$

Here, $\bar{x}_{DualQuintile}$ is average monthly return from following the dual momentum strategy, $\bar{x}_{TraditionalQuintile}$ is average monthly return from following the traditional momentum strategy, and $S_{DualQuintile}$ and $S_{TraditionalQuintil}$ are the standard deviations on the monthly returns of the corresponding quintiles. Each quintile 1 through 5 is tested separately for all three periods considered.

2.2.5 Risk-Adjusted Momentum

The risk-adjusted momentum approach is an attempt to extract the intuition of the dual momentum of only investing a portfolio of stocks if it is favorable compared to a benchmark. The procedure for generaring these portfolios was as follows: (1) calculate 12-month-1-month momentum for each stock; (2) Divide the average momentum measure of the sorted portfolio by the standard deviation of momentum of the same portfolio; (3) calculate 12-month-1 momentum and 12-month-1-month rolling standard deviation for the benchmark; (4) Divide momentum by the standard deviation calculated for the benchmark in order to gather a risk adjusted momentum measure; (5) Invest in the portfolio of stocks if the risk adjusted momentum is higher than the corresponding measure for the benchmark, otherwise invest the full amount in benchmark. As for the case with dual momentum, the SP500 index with ticker 'GSPC' was used as proxy since the ETF did not existed during the entire sample period.

2.3 Transaction Costs

Transcation costs may ruin an otherwise profitable trading strategy; thus transaction costs are an important aspect when doing the evaluation. Even though transaction costs have become much lower more recently, high turnover of the dual momentum strategy may ruin potential benefits of applying the strategy. Therefore, turnover and average monthly returns adjusted for transactions costs are reported in the tables. The following part outlines the methodology of calculating turnover and andjustments of the returs as proposed by Kirby and Osdiek (2015).

The equation below shows turnover at each time t:

$$Turnover_t = \sum_{t=1}^{N} \frac{1}{2} |\hat{w}_{i,t+1} - \hat{w}_{i,t^+}|, \quad (7)$$

where $\hat{w}_{i,t}$ is defined as a portfolio weight in asset i in time t; $\hat{w}_{i,t+1}$ is the weight of asset i after re-balanceing in period $t + 1$; $\hat{w}_{i,t^+}$ is the portfolio weight of asset i in period $t + 1$ before re-balancing.

Portfolio weights before re-balancing can be decomposed as follows:

$$\hat{w}_{i,t+} = \frac{\hat{w}_{i,t}(1 + r_{i,t})}{1 + \sum_{i=1}^{N} \hat{w}_{i,t} r_{i,t}}, \tag{8}$$

where $r_{i,t}$ is defined as return for asset i in period t.

Return adjusted for transaction costs then become:

$$r_{p,t+1} = \sum_{i=1}^{N} \hat{w}_{i,t} r_{i,t+1} - 2 \times c_{i,t} |\hat{w}_{i,t} - \hat{w}_{i,t-1^+}|, \tag{9}$$

where $c_{i,t}$ represents the transaction cost in percentage. The transaction cost is set to $c = 50$ basis points, which is consistent with other literature within the field (see Kirby and Osdiek (2015) and Brant, Santa-Clara, and Valkanov (2009)). The part of the equation adjusting for transaction costs is multiplied by two since turnover is value of both assets purchased and sold.

The equation below describes total turnover for the period:

$$Turnover = \frac{1}{T - L - 1} \sum_{t=L+1}^{T-1} \left(\frac{1}{2} \sum_{i=1}^{N} |\hat{w}_{i,t+1} - \hat{w}_{i,t^+}| \right). \tag{10}$$

Here, T is total number of months used as input when backtesting and L then becomes number of months dropped when doing the calculations. Hence, $T - L$ then becomes actual number of months considered in the test. This is the turnover reported in the tables and returns adjusted for transaction costs are labeled 'MeanTC'.

CHAPTER 3: RESULTS

3.1 Marginal Returns of Stock-Characteristics

To test whether screening enhances performance, an analysis of marginal momentum return of each characteristic, for all the three periods considered, is conducted. Because there has been evidenced a clear break in the profitability of the strategy, there is an increased urgency of examing possibilities to elevate its returns.

Tables 2-4 report descriptive statistics of the portfolios formed by sorting on the residuals from regression 3. For each period considered panels A-D report the mean moments when sorting on respective factor loadings residual. By looking at the tables it becomes clear that only the characteristic in interest changes keeping all others the same as the quintile number varies. This enables examination of momentum profits among these portfolios. If any characteristic strongly correlates with momentum returns, i.e. those obtained when following the momentum strategy, higher profits should be expected when trading stocks with dominance in that characteristic.

The next step in the process is to look at momentum profits within the portfolios created by sorting on the factor loadings residuals. Tables 5-7 report the returns for the 25 portfolios considered for each characteristic for the three periods of interest. Panel A reports returns when the stock universe is initially sorted on the value residual and the effect of momentum is clear troughout the quantiles. Since value is positively correlated with momentum, the highest returns should be expected in the upper left corner in the panel. For the full period 1963-2013 the highest returns are, as expected, found in the upper left corner but the additional gains from the double sorting procedure seem to be higher at lower quantiles of momentum. Looking at the period 1963-1997 average returns in the upper left corner are higher than for the full sample but additional gains from double sorting becomes much lower, even among lower quantiles of momentum. The third period, between 1998 and 2013, exhibit, as recently documented, lower returns in the upper left corner since the momentum strategy has attenuated. It is interesting that gains from the double sorting are higher than during the period 1963-1997. The pattern that becomes visible is that gains from screening for book-to-market increases as momentum returns become lower.

Panel B reports the returns when the stock universe is initially sorted on size. The momentum effect is also clear in this case. Since size is inversly related to mometum, higher profits should be expected at lower quantiles. That implies that the highest returns should be found in the lower left corner of the panel. For the full period 1963-2013 the highest returns are, as expected, found in the lower left corner but the additional gains from the double sorting procedure seems to be higher at lower quantiles of momentum as seen in the case of value. Looking at the period 1963-1997, average returns in the lower left corner are higher than for the full sample but additional gains from double sorting become somewhat lower, even among lower quantiles of momentum. The returns in the lower left corner are lower in the period between 1998 and 2013. This can be explained by attenuation of the momentum strategy. As in the case of value, gains from the double sorting are higher than between 1963 and 1997 and this points to an advantage of double sorting on size as momentum attenuates.

Panel C reports the returns when the stock universe is initially sorted on profitability. The momentum effect is also clear in this case. As in the case of value, profitability is positively correlated with momentum. Hence, the highest returns are expected in the upper left corner in the panel. For the full period 1963-2013 the highest returns are, as expected, found in the upper left corner and the return figures are the highest in absolute value among the portfolios backtested. Additional gains from the double sorting procedure are, as in the previous cases, higher among lower quantiles of momentum. In the period

1963-1997 average returns in the upper left corner are much higher than for the full sample but additional gains from double sorting remain the same for all quantiles of momentum. This differs dramtically from the period between 1998-2013 where retuns were much lower and gains from double sorting increased as lower quantiles of momentum were approached. In summary, there seems to be more gain from double sorting before 1998 than after.

Panel D reports the returns when the stock universe is initially sorted on investments. The effect of momentum is, as it should be, clear. The expectation about correlation between investments was unclear whether it should be positive or negative. That means highest returns should be found either in the upper or lower left corner. Looking at the full sample period between 1963 and 2013 the returns are inversely correlated with momentum even though the relation is unclear among higher quantiles of momentum. As in all previous cases the gains are higher among lower quantiles of momentum. The period between 1963 and 1997 also exhibit the negative relation but returns are higher and gains become larger among lower quantiles of momentum. This is also the case for the period between 1998 and 2013 but with lower returns and increasing gains among lower quantiles of momentum. The results for double sorting on investments are less clear and interpretable but this characteristic may enhance returns.

3.2 Examination of Differences: Stock-Characteristics

From the outline of the results above there may be gains from applying a screening procedure but in order to properly decide, a statistical method should be employed. The method used is the t-test described earlier in equation 4.

Table 11 reports t statistics for the hedge portfolios, quintile 1 - quintile 5, considered. The t-statistics are dispersed across the periods and quantiles except for gross profitability, which is significant for all quantiles in all periods at the 95 percent confidence level. There also seems to exist benefits of screening at lower quantiles of momentum, i.e. when the momentum effect is weak. This can be justified by higher t-statistics at lower quantiles.

Looking at the difference between the periods 1963-1997 and 1998-2013, the t-statistics are generally higher for the second period suggesting that the impact of screening becomes more prominent as momentum returns attenuate. However, the only characteristic that showed clear enhancement is gross profitability.

3.3 Marginal Return of Idiosyncratic Risk

An extension to the testing when screening for stock characteristics, Ivol, was tested. Table 13 reports descriptive statistics of the portfolios formed by sorting on the residuals from regression 3. The panels A-D report the mean moments of each period considered when sorting on the factor loadings residuals of Ivol. In the tables, it becomes clear that only the characteristic of interest changes keeping all others the same as quintile number varies. This enables examination of momentum profits among these portfolios.

The next step in the process is to look at momentum profits within the portfolios created by sorting on the factor loadings residuals. Table 14 reports the returns for the 25 portfolios considered for each period in interest. For the full sample period there is a positive correlation between momentum and Ivol for momentum quantiles 1 and 2. The case is rather the opposite for quintile 3-5. This is the same for the period 1964-1997 but in the period 1998-2013 the correlation is positive for all quantiles. Overall the differences throughout the Ivol quantiles are small and this suggests, along with the fact that the correlation is inconsistent, that conditioning on Ivol will not elevate returns.

3.4 Examination of Differences: Idiosyncratic Risk

Table 15 reports t-statistics for the hedge portfolios based on ivol for the periods considered. The fact that only a few of the t-stats are significant along with the previous insight of a reverse correlation, of what was expected, suggests that ivol should not be used to elevate returns. Previous research has drawn attention to idiosyncratic volatility as an explanation of the persistence of the momentum strategy but when looking at the marginal return of this characteristic, no relationship seems to exist. This goes against the evidence presented in earlier literature.

3.5 Dual Momentum

Dual momentum was shown to be successful for only an extremely small number of stocks, which is why interest arose to extend the strategy to a larger universe of stocks. Table 8 and 9 report descriptive statistics when following traditional and dual momentum respectively.

Average monthly returns of the top quintile seem to be the same for traditional and dual momentum throughout all sample periods; the returns are even slightly lower following the dual momentum strategy. Looking at the full sample period between 1965 and 2013, gains from trading using dual momentum appear to be magnified at lower quantiles. Mean return for quintile 5 in the full sample period and 1965-1997 take rather extreme proportions but could be due to outliers that were not excluded when the top/bottom 1 percent was removed. This pattern is even more accentuated during the period 1965-1997 but is non-existant in 1998-2013. In fact, dual momentum performs worse throughout all quantiles. The pattern of generally lower average returns during the period 1998-2013 holds here.

Regarding standard deviations, the same pattern appears as for monthly average returns. The standard deviations are the same, even lower, for dual than traditional momentum but become smaller for lower quantiles. The most dramatic differences are for quintile 5 for the full sample period and 1965-1997. It seems like the standard deviations approach that of the benchmark for lower quantiles as the number of months where the full amount is invested in benchmark increases. This is completely the case for the period 1998-2013 quintile 5 where only stocks entered the portfolio in four months. The pattern of generally higher standard deviations during the period after 1997 can be confirmed.

Maximum drawdown is slightly lower for dual momentum quintile 1 for all sample periods but decreases dramatically for lower quantiles in dual momentum opposed to traditional where they increase as lower quantiles are approached. The same conclusion as drawn earlier about approaching benchmark descriptives applies here too. Maximun drawdown following dual momentum approaches benchmark as frequancy of number of months investing in bench increases. The turnover seems to increase for lower quantiles but since transaction costs were set to 0.5, which is consistent with other literature within the field, average montly return is almost not affected at all.

3.6 Examination of Differences: Dual Momentum

From the outline of the results above there may be gains from applying dual momentum for lower quantiles but in order to properly decide a statistical method needs to be employed. The method used is the t-test described earlier in equation 4.

Table 12 reports t-statistics of the diffence in monthly average return for each quintile. For the full sample between 1965 and 2013 and for the period 1965-1997 quintile 4-5 shows statistically signifcant improvment from following the dual momentum strategy at the 95 percent level of confidence. The period between 1998 and 2013 showed no significant improvment at all.

The expected outcome from following the dual momentum approach, significantly higher returns, lower standard deviation, and drawdowns at higher quantiles, cannot be confirmed. Hence, trading using the dual momentum approach is not likely to improve profits. One reason why the strategy does not work is that momentum profits are driven by exposure to volatility. Yet that exposure is limited by allowing for the position taking in a benchmark that limits that exposure.

3.7 Risk-Adjusted Momentum

The risk-adjusted momentum approach is an attempt to extract the intuition behind dual momentum of only investing in a portfolio of stocks if it is favorable compared to a benchmark. Table 10 reports mean moments when following during the periods 1965-2013, 1963-1997, and 1998-2013. The risk-adjusted momentum approach resulted in lower average monthly returns than traditional for all quantiles all periods considerd. Interestingly the volatility became much lower throughout all quantiles but turnover remained roughly the same. A more proper way that could work better is by comparing the rolling 12-month-

1-month Sharpe ratio of benchmark with the same of the portfolio instead of average Sharpe ratio, which was used in this case. In summary, this strategy does not seem to serve the purpose of elevating the momentum returns.

3.8 An Elevating Strategy

The analysis above can be summarized as that the only variable that could be attributed to higher momentum returns is gross profitability and that dual momentum applied on a larger stock universe does not improve performance. This implies that a strategy where the stock universe is narrowed through a screening process based on gross profitability could result in higher momentum returns.

Table 16 reports descriptives when following a strategy that implies narrowing down the stock universe based on the gross profitability measure. For each of the periods 1963-1997 and 1998-2013, the stock universe was first narrowed based on profitability rank. The top 50 percent, top 25 percent, and top 10 percent were tested separately. Then within this selected universe top 20 percent of the stocks are choosen accoring to the 12-month-1-month momentum measure. In order to make the outcome comparable, one portfolio is created where top 20 percent based on momentum is selected directly. The portfolios were monthly rebalanced.

For the period 1963-1997 returns increase as the universe is narrowed, as expected, but the volatility also increased. This means that the risk-adjusted returns remain roughly the same. This is also the case for the period 1998-2913 but here there is a break in the effect. Choosing the top 25 percent based on gross profitability actually generates slightly lower returns than of the top 50 percent but still remains higher than using the full universe. This suggests that there cannot be any expected benefit from trading following the momentum strategy where the stock univere is scrrened for gross profitability.

The major insight from the analysis is that if the only difference between two stocks is the level of gross profitability, the one with higher gross profitability is expected to exhibit higher momentum return. That a strategy that involves screening for gross profitability does not improve the results may be explained by covariation with other characteristics that pressures down the momentum.

Fama and French (1992) suggested herding behavior as an explanation of the momentum anomaly. The findings in this paper may be interpreted as support for a herding behavior in the sense that investors only look at the direction of price development. They simply follow the crowd ignoring the fundamentals. This suggests that further research may be focused on predictability of persistence of strong price movments. Elaboration with trading volume could be a starting point.

CHAPTER 5: CONCLUSION

The documented attenuation of the momentum strategy urges finding ways to elevate the returns to this strategy. The purpose of this paper was to look into ways to achieve that. Much of the literature about enhanced momentum identifies certain stock characteristics that are strongly correlated with momentum returns. Recently, high ididosyncratic risk has been suggested as a common source. This paper aimed to examine the relation between stock characteristics and momentum returns by applying a different approach than the rest of the literature. Portfolios were constructed where the only difference was variation in a particular characteristic, holding all other characteristics the same. This facilitated looking at the impact on momentum profits given change in only one characteristic.

An alternative technique is the dual momentum strategy, which has proven to work well for an extremely small selection of stocks. The attractiveness of looking into this strategy was its simplicity coupled with its potential high performance. Backtesting on a larger universe of stocks was therefore a natural extension. In this approach, a position was taken if a stock was top performer and exhibited higher momentum than a benchmark, here the SandP500 index. Otherwise, the full amount was invested in the benchmark until next evaluation date.

Equity data were gathered from Center for Research in Security Prices (CRSP). Market returns were collected from Kenneth French website. The sample includes common equity securities listed on NYSE, NASDAQ, and AMEX between 1963 and 2013. Stock characteristics considered are book-to-market ratio, market size as a proportion of market equity, profitability measured as gross return divided by total assets, and investments as a proportion of the growth in total assets from the previous fiscal year. All characteristics were lagged to ensure they were known at the decision date. In addition to these characteristics a measure of idiosyncratic risk was calculated using the equity data and market returns.

The analysis showed that if the only difference between two stocks is the level of gross profitability then the stock with higher gross profitability is expected to exhibit higher momentum return. No other characteristis considered seemed to elevate the momentum returns. When backtesting a strategy where the stock universe first was screened for gross profitability before applying the momentum approach the performance did not improve, which may be explaind by covariation with other characteristics that pressures down the momentum.

The findings in this paper may support herding behavior in the sense that investors only look at the direction of price development. This means that investors may tend to ignore fundamentals and choose only to follow the crowd. Further research may therefore be focused on predictability of persistence of strong price movments. Elaboration with trading volume could be a starting point. Skewness as measure of probability of future returns is another potential source of gains since evidence has been presented suggesting a positive relation between stocks with negatively skewed returns and momentum.

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APPENDIX A: TABLES

Table 1: General descriptive statistics

The table reports general statistics of the aggregated data set.

Panel A: Means and percentiles

		Percentiles						
Stat	Mean	1st	10th	25th	50th	75th	90th	99th
$BEME$	-0.52	-2.93	-1.65	-1.02	-0.44	0.06	0.48	1.19
ME	4.75	0.67	2.13	3.23	4.63	6.19	7.51	9.67
GP	0.33	-0.2	0.04	0.13	0.3	0.48	0.68	1.08
INV	0.22	-0.36	-0.09	0	0.09	0.23	0.54	2.88
Ret	1.27	-35.84	-14.17	-6.19	0	7.21	16.67	51.61
$R_{12,2}$	0.12	-0,75	-0.42	-0.19	0.06	0.33	0.69	0.93

Panel B: Correlations

Stat	$BEME$	ME	GP	INV	Ret	$R_{12,2}$
$BEME$	1	-0.32	-0.16	-0.18	-0.13	0.03
ME	-0.32	1	-0.11	0.03	0.06	-0.02
GP	-0.16	-0.11	1	-0.06	0.04	0.01
INV	-0.18	0.03	-0.06	1	-0.07	-0.03
Ret	-0.13	0.06	0.04	-0.07	1	0.01
$R_{12,2}$	0.03	-0.02	0.01	-0.03	0.01	1

Panel C: Standard Deviations

		Percentiles						
Stat	Full sample	1st	10th	25th	50th	75th	90th	99th
$BEME$	0.85	0.81	0.66	0.54	0.42	0.33	0.27	0.19
ME	2.05	2.01	1.82	1.6	1.3	1	0.79	0.35
GP	0.26	0.25	0.24	0.22	0.2	0.17	0.14	0.06
INV	0.68	0.68	0.7	0.75	0.88	1.16	1.6	2.92
Ret	16.11	15.45	14.25	14.1	15.23	18.15	23.64	47.12
$R_{12,2}$	0.52	0.52	0.49	0.48	0.5	0.56	0.66	0.96

Table 2: Portfolio descriptives full sample

The table reports descriptive statistics for each portfolio sorted on factor loading residuals. To generate the portfolios, each characteristic was regressed using equation 3. The portfolios in this table were then created by sorting on the residuals from the regression, not the characteristics. For this table the full sample was considered, which is July 1963-December 2013

Panel A: Firms grouped by BEME residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	1.5015	5.9155	0.1255	7.4261	0.3542	4.5418	0.3321	0.2449
2	1.3887	5.3504	-0.1964	6.8157	-0.1124	4.8234	0.3133	0.1787
3	1.2739	5.2740	-0.3604	6.6774	-0.4210	4.8491	0.3179	0.1919
4	1.1820	5.6978	-0.3015	6.1514	-0.8079	4.8642	0.3488	0.2341
5	0.9335	6.9031	-0.2289	5.3813	-1.6282	4.6729	0.3480	0.2658

Panel B: Firms grouped by ME residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	1.1031	4.9875	-0.3110	5.7928	-0.5667	7.3929	0.3168	0.1741
2	1.2505	5.7284	-0.3401	6.1774	-0.5580	5.6935	0.3429	0.2515
3	1.2343	6.0983	-0.2160	6.0319	-0.4816	4.5988	0.3495	0.2763
4	1.2312	6.2292	-0.0773	6.1113	-0.4418	3.6176	0.3311	0.2417
5	1.4612	6.8918	0.3723	6.2078	-0.5659	2.4454	0.3198	0.1720

Panel C: Firms grouped by GP residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	1.5181	6.0599	-0.0987	6.2918	-0.6574	4.5883	0.7168	0.2065
2	1.3646	6.0619	-0.2528	5.9273	-0.5234	4.7750	0.4355	0.2472
3	1.2144	6.0352	-0.2724	6.2388	-0.4374	4.8765	0.2985	0.2470
4	1.1688	5.4987	-0.2123	5.9895	-0.3410	5.0449	0.1655	0.2218
5	1.0135	5.3089	-0.2023	6.1155	-0.6548	4.4664	0.0435	0.1929

Panel D: Firms grouped by INV residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	0.8691	6.7791	-0.0608	6.2344	-0.6147	4.5379	0.3501	0.8868
2	1.3253	5.5105	-0.1832	6.8324	-0.3018	4.8384	0.3724	0.1726
3	1.3318	5.0651	-0.3241	6.6604	-0.3387	5.0457	0.3324	0.0913
4	1.3732	5.1272	-0.4351	6.2483	-0.4680	4.9948	0.3154	0.0396
5	1.3808	6.4824	-0.0918	5.3940	-0.8910	4.3344	0.2898	-0.0754

Table 3: Portfolio descriptives 1963-1997

The table reports descriptive statistics for each portfolio sorted on factor loadings residuals. To generate the portfolios, each characteristic was regressed using equation 3. The portfolios in this table were then created by sorting on the residuals from the regression, not the characteristics. For this table stocks traded between July 1963 and December 1997 were considered.

Panel A: Firms grouped by BEME residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	1.5449	5.5246	0.3497	8.4082	0.4135	3.8744	0.3640	0.2280
2	1.4567	5.2220	-0.0357	7.8930	-0.0155	4.3108	0.3314	0.1681
3	1.3421	5.2562	-0.3352	7.5292	-0.3250	4.3647	0.3446	0.1852
4	1.2143	5.6309	-0.39177	6.47042	-0.7153	4.3354	0.3789	0.2247
5	0.9992	6.4544	-0.3291	5.3331	-1.5180	4.0481	0.3723	0.2447

Panel B: Firms grouped by ME residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	1.1728	4.6837	-0.1870	6.0664	-0.4596	6.8130	0.3418	0.1624
2	1.2817	5.3921	-0.3563	7.2392	-0.4663	5.1345	0.3608	0.2388
3	1.2833	5.7804	-0.2418	7.1002	-0.3889	4.0314	0.3743	0.2536
4	1.2543	6.2100	-0.0555	6.6953	-0.3766	3.0612	0.3704	0.2344
5	1.5659	6.7592	0.2911	5.7497	-0.4676	1.8898	0.3440	0.1616

Panel C: Firms grouped by GP residual

	Sample moments of return				Sample means of characteristics			
Quantile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	1.4989	5.7250	-0.2008	6.7920	-0.5628	4.0946	0.7388	0.2068
2	1.3705	5.7891	-0.2480	6.7252	-0.4249	4.1888	0.4595	0.2198
3	1.2732	5.8089	-0.2079	6.9928	-0.3388	4.1675	0.3242	0.2204
4	1.2993	5.4881	-0.0534	6.5449	-0.2685	4.4307	0.1944	0.2064
5	13.3809	18.0370	-0.2019	6.8520	-0.5640	4.0517	0.0738	0.1973

Panel D: Firms grouped by INV residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	0.9775	6.4694	-0.1061	6.2449	-0.5427	3.9307	0.3746	0.7865
2	1.3815	5.2906	-0.1636	7.1740	-0.1897	4.4043	0.3830	0.1728
3	1.3941	4.9481	-0.2051	7.3648	-0.2390	4.6016	0.3540	0.0971
4	1.4369	5.0492	-0.3877	7.2400	-0.3751	4.4215	0.3490	0.0490
5	1.3676	6.1800	-0.0908	6.4227	-0.8127	3.5750	0.3306	-0.0552

Table 4: Portfolio descriptives 1998-2013

The table reports descriptive statistics for each portfolio sorted on factor loadings residuals. To generate the portfolios each characteristic was regressed using equation 3. The portfolios in this table were then created by sorting on the residuals, not the characteristics. For this table stocks traded between January 1998 and December 2013 were considered

Panel A: Firms grouped by BEME residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	1.4080	6.6957	-0.1374	5.9114	0.2579	5.6267	0.2803	0.2724
2	1.2418	5.6285	-0.4630	4.9590	-0.2699	5.6565	0.2838	0.1960
3	1.1270	5.3230	-0.4115	4.9173	-0.5768	5.6364	0.2744	0.2029
4	1.1124	5.8537	-0.1247	5.5494	-0.9585	5.7237	0.3000	0.2495
5	0.7919	7.7996	-0.0827	5.0787	-1.8073	5.6883	0.3085	0.3002

Panel B: Firms grouped by ME residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	0.9529	5.5969	-0.4371	5.1199	-0.7408	8.3357	0.2762	0.1932
2	1.1832	6.4083	-0.3021	4.6652	-0.7071	6.6022	0.3140	0.2721
3	1.1285	6.7476	-0.1645	4.4978	-0.6321	5.5210	0.3092	0.3133
4	1.1813	6.2863	-0.1224	4.9017	-0.5479	4.5221	0.2671	0.2535
5	1.2355	7.1822	0.5291	6.9781	-0.7258	3.3482	0.2804	0.1887

Panel C: Firms grouped by GP residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	1.5595	6.7414	0.0339	5.3947	-0.8112	5.3910	0.6810	0.2060
2	1.3518	6.6277	-0.2545	4.6960	-0.6836	5.7280	0.3964	0.2918
3	1.0877	6.5105	-0.3570	5.0158	-0.5977	6.0290	0.2566	0.2904
4	0.8875	5.5253	-0.5489	4.7381	-0.4588	6.0432	0.1184	0.2469
5	0.7945	5.5301	-0.1898	4.8183	-0.8024	5.1404	-0.0058	0.1858

Panel D: Firms grouped by INV residual

	Sample moments of return				Sample means of characteristics			
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV
1	0.6355	7.4155	0.0276	6.0021	-0.7317	5.5251	0.3102	1.0499
2	1.2041	5.9697	-0.1976	6.1619	-0.4841	5.5441	0.3551	0.1723
3	1.1973	5.3196	-0.5202	5.4074	-0.5007	5.7675	0.2973	0.0819
4	1.2357	5.3021	-0.5163	4.4319	-0.6191	5.9265	0.2608	0.0244
5	1.4092	7.1077	-0.0947	3.9043	-1.0181	5.5685	0.2235	-0.1082

Table 5: Mean returns of double sorted portfolios full sample

The table reports mean returns of portfolios double sorted on residuals of respective characteristic and then momentum. The procedure for generating these portfolios was as follows: (1) Form portfolios by sorting on the residuals from equation 3. These are presented in table 2-4. (2) Sort a second time, but now on the 12-month-1-month momentum measure calculated for each individual stock. The portfolios were monthly rebalanced. For this table, the full sample was considered, which is July 1963-December 2013.

Panel A: BEME

BEME \ Mom	1	2	3	4	5	H-L
1	1.9163	1.6244	1.4430	1.4342	1.0866	0.8296
2	1.7969	1.4360	1.3173	1.2929	1.0971	0.6998
3	1.8044	1.3828	1.2304	1.0737	0.8737	0.9308
4	1.7997	1.4279	1.1001	0.8316	0.7462	1.0535
5	1.6511	1.2464	0.8071	0.6150	0.3423	1.3088
H-L	0.2651	0.3780	0.6358	0.8191	0.7443	

Panel B: ME

ME \ Mom	1	2	3	4	5	H-L
1	1.3473	1.1335	1.0533	1.0897	0.8904	0.4569
2	1.6710	1.3458	1.2034	1.1220	0.9074	0.7636
3	1.7933	1.4622	1.2606	1.0396	0.6107	1.1826
4	1.9093	1.4450	1.2404	0.9901	0.5658	1.3435
5	1.7476	1.6185	1.3161	1.2025	1.4199	0.3277
H-L	-0.4002	-0.4850	-0.2628	-0.1127	-0.5295	

Panel C: GP

GP \ Mom	1	2	3	4	5	H-L
1	1.9875	1.5690	1.3890	1.3391	1.3036	0.6839
2	1.8781	1.4397	1.2905	1.1068	1.1046	0.7735
3	1.6560	1.4191	1.2304	1.0154	0.7472	0.9088
4	1.7446	1.3801	1.1325	0.9767	0.6057	1.1389
5	1.5010	1.1869	1.0106	0.7681	0.5971	0.9039
H-L	0.4864	0.3821	0.3784	0.5710	0.7065	

Panel D: INV

INV \ Mom	1	2	3	4	5	H-L
1	1.6479	1.1920	0.8904	0.5082	0.1010	1.5470
2	1.8125	1.4320	1.2421	1.1076	1.0279	0.7845
3	1.7821	1.3514	1.2284	1.1715	1.1223	0.6598
4	1.7621	1.4580	1.2492	1.1888	1.2051	0.5570
5	1.7242	1.4900	1.2107	1.1260	1.3506	0.3736
H-L	-0.0762	-0.2981	-0.3202	-0.6177	-1.2496	

Table 6: Mean returns of double sorted portfolios 1963-1997

The table reports mena returns of portfolios double sorted on residuals of respective characteristic and then momentum.The procedure for generating these portfolios was as follows: (1) Form portfolios by sorting on the residuals from equation 3. These are presented in table 2-4. (2) Sort a second time, but now on the 12-month-1-month momentum measure calculated for each individual stock. The portfolios were monthly rebalanced. For this table stocks traded between July 1963 and December 1997 were considered.

Panel A: BEME

BEME \ Mom	1	2	3	4	5	H-L
1	1.9827	1.7152	1.5534	1.4941	0.9742	1.0085
2	1.8880	1.6289	1.4226	1.3538	0.9853	0.9027
3	1.9656	1.5100	1.2953	1.1574	0.7753	1.1903
4	1.9263	1.4838	1.1391	0.8437	0.6724	1.2539
5	1.8898	1.3224	0.8190	0.6560	0.3013	1.5885
H-L	0.0929	0.3928	0.7344	0.8381	0.6729	

Panel B: ME

ME \ Mom	1	2	3	4	5	H-L
1	1.4908	1.2412	1.0710	1.1309	0.9277	0.5631
2	1.8553	1.4496	1.2562	1.1565	0.6858	1.1695
3	1.9415	1.5613	1.3544	1.0984	0.4539	1.4876
4	1.9656	1.4895	1.3338	1.0564	0.4186	1.5470
5	1.8336	1.7028	1.4384	1.4512	1.4008	0.4328
H-L	-0.3427	-0.4616	-0.3674	-0.3203	-0.4731	

Panel C: GP

GP \ Mom	1	2	3	4	5	H-L
1	2.1099	1.6294	1.4321	1.2938	1.0248	1.0851
2	1.9667	1.5091	1.3647	1.1377	0.8690	1.0977
3	1.7723	1.4898	1.2792	1.1257	0.6934	1.0788
4	1.9510	1.4989	1.2295	1.0939	0.7170	1.2340
5	1.7017	1.3064	1.1234	0.8412	0.5968	1.1049
H-L	0.4082	0.3230	0.3087	0.4526	0.4280	

Panel D: INV

INV \ Mom	1	2	3	4	5	H-L
1	1.8394	1.3381	1.0285	0.5865	0.0865	1.7528
2	1.9317	1.5090	1.3698	1.2078	0.8827	1.0490
3	1.9009	1.4621	1.3410	1.2206	1.0414	0.8595
4	1.9424	1.5777	1.3407	1.2346	1.0844	0.8580
5	1.8437	1.4823	1.1753	1.0971	1.2353	0.6084
H-L	-0.0043	-0.1442	-0.1467	-0.5106	-1.1487	

Table 7: Mean returns of double sorted portfolios 1998-2013

The table reports mena returns of portfolios double sorted on residuals of respective characteristic and then momentum.The procedure for generating these portfolios was as follows: (1) Form portfolios by sorting on the residuals from equation 3. These are presented in table 2-4. (2) Sort a second time, but now on the 12-month-1-month momentum measure calculated for each individual stock. The portfolios were monthly rebalanced. For this table stocks traded between January 1998 and December 2013 were considered.

Panel A: BEME

BEME \ Mom	1	2	3	4	5	H-L
1	1.7731	1.4287	1.2048	1.3049	1.3290	0.4440
2	1.6004	1.0200	1.0902	1.1617	1.3383	0.2621
3	1.4569	1.1083	1.0905	0.8931	1.0857	0.3712
4	1.5269	1.3073	1.0162	0.8057	0.9054	0.6215
5	1.1366	1.0827	0.7815	0.5267	0.4308	0.7058
H-L	0.6365	0.3459	0.4233	0.7782	0.8983	

Panel B: ME

ME \ Mom	1	2	3	4	5	H-L
1	1.0379	0.9013	1.0151	1.0009	0.8100	0.2279
2	1.2738	1.1219	1.0896	1.0476	1.3854	-0.1116
3	1.4737	1.2484	1.0582	0.9130	0.9488	0.5249
4	1.7879	1.3489	1.0391	0.8469	0.8831	0.9048
5	1.5621	1.4367	1.0523	0.6661	1.4612	0.1010
H-L	-0.5242	-0.5354	-0.0372	0.3348	-0.6512	

Panel C: GP

GP \ Mom	1	2	3	4	5	H-L
1	1.7234	1.4388	1.2961	1.4367	1.9047	-0.1813
2	1.6870	1.2900	1.1305	1.0401	1.6126	0.0744
3	1.4053	1.2667	1.1251	0.7776	0.8631	0.5422
4	1.2995	1.1241	0.9234	0.7239	0.3657	0.9338
5	1.0682	0.9292	0.7674	0.6104	0.5977	0.4705
H-L	0.6552	0.5096	0.5288	0.8263	1.3070	

Panel D: INV

INV \ Mom	1	2	3	4	5	H-L
1	1.2352	0.8769	0.5926	0.3395	0.1321	1.1030
2	1.5554	1.2661	0.9667	0.8915	1.3411	0.2143
3	1.5260	1.1127	0.9855	1.0656	1.2967	0.2293
4	1.3733	1.1997	1.0518	1.0902	1.4652	-0.0919
5	1.4665	1.5068	1.2870	1.1881	1.5992	-0.1327
H-L	-0.2313	-0.6299	-0.6944	-0.8487	-1.4670	

Table 8: Traditional momentum

The table reports descriptive statistics of portfolios following the traditional momentum approah. Here, the 12-month-1-month momentum statistic was calculated for each stock. In the beginning of each month the portfolios were evaluated and rebalanced such that only the stocks falling within respective quintile were included in the portfolio.

Panel A: Full sample

Quintile	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
1	1.7701	6.2901	-0.5225	5.7896	44.0043	0.2665	1.7590
2	1.4249	5.1209	-0.6003	6.6892	43.0180	0.4786	1.4050
3	1.1878	5.0932	-0.4485	7.1085	42.7419	0.5202	1.1662
4	1.0581	5.8923	0.0545	7.0099	44.0924	0.4738	1.0384
5	0.8381	8.1631	1.0925	10.4165	53.5677	0.2660	0.8270

Panel B: 1965-1997

Quantile	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
1	1.9372	6.1633	-0.7054	6.1503	44.0043	0.2650	1.9261
2	1.5106	5.2740	-0.5395	7.4083	43.0180	0.4789	1.4907
3	1.2878	5.1513	-0.3060	7.6124	42.7419	0.5219	1.2661
4	1.1195	5.6446	0.1515	7.2839	44.0924	0.4779	1.0996
5	0.7365	7.0892	0.6323	7.0438	49.9274	0.2692	0.7252

Panel C: 1998-2013

Quintile	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
1	1.4290	6.5447	-0.1934	5.2627	37.2432	0.2697	1.4178
2	1.2500	4.8018	-0.7840	4.3515	25.3771	0.4781	1.2300
3	0.9837	4.9794	-0.7821	5.8473	30.0784	0.5168	0.9621
4	0.9329	6.3819	-0.0711	6.4368	39.3092	0.4656	0.9135
5	1.0455	10.0228	1.3152	10.3280	53.5677	0.2597	1.0347

Table 9: Dual momentum

The table reports descriptive statistics for portfolios following the dual momentum approach. In the beginning of each month all stocks were sorted on their respective 12-month-1-month momentum measure. Those stocks, within the sorted portfolio, with a momentum measure higher than the corresponding for benchmark entered the portfolio. If momentum for chosen benchmark was higher than any stock the current month, the full amount was invested the bench until next evaluation date. Since the SP500 ETF not has existed during the whole sample period the benchmark used was a proxy for the index with ticker 'GSPC'.

Panel A: Full sample

Quintile	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
1	1.7634	6.2459	-0.5279	5.8412	44.0043	0.2665	1.7523
2	1.4337	5.1247	-0.6046	6.7253	43.2291	0.5123	1.4124
3	1.3602	4.7240	-0.0682	7.1471	38.1592	0.6747	1.3321
4	1.4352	4.6316	-0.2280	5.2555	28.4770	0.7851	1.4025
5	2.4909	4.8411	1.0507	4.8312	17.9989	0.9509	2.4512

Panel B: 1965-1997

Quintile	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
1	1.9372	6.1630	-0.7056	6.1514	44.0043	0.2650	1.9261
2	1.5063	5.2689	-0.5626	7.5418	43.2291	0.5168	1.4847
3	1.4528	4.7071	0.4181	7.5478	35.6490	0.6756	1.4247
4	1.4877	4.5715	-0.1429	6.1392	28.4770	0.7581	1.4561
5	3.1733	4.3546	1.7166	5.5814	12.8536	0.9464	3.1339

Panel C: 1998-2013

Quintile	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
1	1.4384	6.5280	-0.1980	5.2897	37.2432	0.2703	1.4271
2	1.2823	4.8821	-0.7428	4.3169	26.6894	0.5028	1.2614
3	1.1363	5.0484	-1.1250	6.3348	28.6276	0.6707	1.1084
4	1.1058	4.8998	-0.2906	3.1848	19.3245	0.8438	1.0707
5	0.6261	4.3829	-0.4295	4.7537	21.7630	<0.01	0.6261

Table 10: Risk-adjusted momentum

This an attempt to create an alternative version of the duam momentum approach. The procedure for generaring these portfolios was as follows: (1) calculate 12-month-1-month momentum for each stock and sort on the same measure. (2) Divide the mean momentum measure, of the sorted portfolio, with the standard deviation of momentum of the same portfolio. We now have one risk adjusted momentum measure for each month. (3) calculate 12-month-1 momentum and 12-month-1-month rolling standard deviation for the benchmark. (4) Divide momentum and standar deviated calculated for the benchmark in order to gather a risk adjusted momentum measure. (4) Invest in the portfolio of stocks if the risk adjusted momentum is higher than the corresponding for benchmark, otherwise invest the full amount in bench. Since the SP500 ETF not has existed during the whole sample period the benchmark used was a proxy for the index with ticker 'GSPC'.

Panel A: Full sample

Quintile	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
1	1.3709	5.3837	-0.0549	5.1224	35.5953	0.2665	1.3598
2	1.2664	4.7579	-0.5493	8.1562	43.0180	0.4786	1.2465
3	0.7303	3.2511	0.2794	9.3628	32.2955	0.5202	0.7086
4	0.2588	2.0319	1.9597	27.5811	28.0310	0.4738	0.2390
5	0.0992	1.3043	19.0179	401.0973	22.3904	0.2660	0.0881

Panel B: 1965-1997

Quantile	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
1	1.5522	5.2759	0.1122	5.0041	35.5953	0.2650	1.5411
2	1.3352	5.0324	-0.5133	8.6591	43.0180	0.4789	1.3152
3	0.8175	3.3190	0.3502	10.6434	32.2955	0.5219	0.7958
4	0.3080	2.0438	2.2219	31.1307	28.0310	0.4779	0.2881
5	0.0721	0.6615	11.0236	127.5188	8.1864	0.2692	0.0609

Panel C: 1998-2013

Quintile	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
1	1.001	5.593	-0.321	5.189	32.599	0.270	0.989
2	1.126	4.150	-0.703	4.748	23.877	0.478	1.106
3	0.552	3.109	0.079	5.810	17.094	0.517	0.531
4	0.158	2.009	1.399	19.749	19.251	0.466	0.139
5	0.084	3.306	2.461	35.605	32.425	0.260	0.073

Table 11: T-statistics stock-screening

The table reports t-statistics for the hedge portfolios for respective quintile. The stats were calculated using equation 4 such that all High-Low (quintile 1-quantile5) for momentum were considered. For example, BEME quintile 1 in panel A was calculated using $\bar{x}_{High}$ equal to BEME1/Mom1 in table 5 and $\bar{x}_{Low}$ equal to BEME5/Mom1 in the same table. The t-stat for BEME quintile 2 was calculated using $\bar{x}_{High}$ equal to BEME1/Mom2, $\bar{x}_{Low}$ equal to BEME5/Mom2 etc. By doing this, it becomes posible to say whether the double sorting procedure has any significant impact on the returns.

Panel A: Full sample

MomQuintile	1	2	3	4	5
BEME	1.814	2.733	4.534	5.464	4.347
ME	2.813	3.627	1.956	0.792	3.196
GP	3.342	2.954	2.961	4.120	4.243
INV	0.503	2.102	2.259	4.098	7.180

Panel B: 1963-1997

MomQuintile	1	2	3	4	5
BEME	0.535	2.374	4.454	4.825	3.517
ME	2.014	2.837	2.250	1.907	2.554
GP	2.368	2.055	1.999	2.764	2.440
INV	0.024	0.840	0.864	2.896	5.865

Panel C: 1998-2013

MomQuintile	1	2	3	4	5
BEME	2.393	1.390	1.628	2.739	2.656
ME	2.621	2.939	0.200	1.624	2.510
GP	2.458	2.262	2.347	3.245	3.996
INV	0.838	2.531	2.727	3.012	4.298

Table 12: T-statistics dual vs. traditional momemtum

The table reports t-statistics for difference in performance between dual and traditional momentum for each quintile. The method is described in equation 6.

Quintile	1965-2011	1965-1997	1998-2013
1	-0.046	0.001	0.036
2	0.066	-0.027	0.144
3	1.326	1.038	0.666
4	2.802	2.275	0.712
5	11.048	14.226	-1.527

Table 13: Portfolio descriptives ivol

The table reports descriptive statistics for each portfolio sorted on factor loadings residuals. To generate the portfolios Ivol was regressed using equation 3. The portfolios in this table were then created by sorting on the ivol residuals, not the characteristics.

Panel A: Full sample period

	Sample moments of return				Sample means of characteristics				
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV	Ivol
1	1.3029	7.2849	0.0605	5.7027	-0.4350	4.6145	0.3301	0.1494	16.6251
2	1.3427	5.9002	-0.3586	5.7406	-0.4743	5.3156	0.3352	0.1606	11.2093
3	1.2907	5.2733	-0.3813	6.5879	-0.4926	5.5224	0.3359	0.1523	8.8549
4	1.3200	4.7447	-0.4450	7.0347	-0.4894	5.3322	0.3321	0.1483	7.2725
5	1.3287	4.0520	-0.4608	7.9806	-0.4104	4.4045	0.3242	0.1431	5.5956

Panel B: 1964-1997

	Sample moments of return				Sample means of characteristics				
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV	Ivol
1	1.2530	6.6584	-0.0413	6.5023	-0.3329	4.0468	0.3599	0.1498	15.3176
2	1.3784	5.6836	-0.3540	6.3212	-0.3720	4.8083	0.3568	0.1576	10.4296
3	1.3532	5.2391	-0.3098	7.0773	-0.3900	4.9883	0.3596	0.1525	8.3719
4	1.4286	4.8324	-0.2603	7.4077	-0.3789	4.7663	0.3579	0.1514	7.0235
5	1.4801	4.2519	-0.3308	8.1968	-0.3130	3.8865	0.3568	0.1441	5.5235

Panel C: 1998-2013

	Sample moments of return				Sample means of characteristics				
Quintile	Mean	Std	Skewness	Kurtosis	BEME	ME	PROF	INV	Ivol
1	1.4075	8.4659	0.1481	4.4944	-0.5920	5.4869	0.2843	0.1488	18.6341
2	1.2680	6.3446	-0.3550	4.8014	-0.6315	6.0949	0.3020	0.1651	12.4071
3	1.1600	5.3556	-0.5193	5.6208	-0.6503	6.3428	0.2996	0.1521	9.5970
4	1.0926	4.5596	-0.9269	5.8782	-0.6591	6.2014	0.2925	0.1436	7.6550
5	1.0118	3.5876	-1.0153	6.1756	-0.5601	5.2002	0.2743	0.1416	5.7063

Table 14: Mean returns of double sorted portfolios on ivol

The table reports mean returns of portfolios double sorted on residuals of ivol and then momentum.The procedure for generating these portfolios was as follows: (1) Form portfolios by sorting on the residuals from equation 3. These are presented in table 13. (2) Sort a second time, but now on the 12-month-1-month momentum measure calculated for each individual stock. The portfolios were monthly rebalanced.

Panel A: Full sample

Ivol \ Mom	1	2	3	4	5	H-L
1	2.0325	1.5852	1.2289	1.0192	0.6405	1.3920
2	1.8858	1.5376	1.2671	1.0717	0.9453	0.9405
3	1.7657	1.3097	1.1780	1.1183	1.0787	0.6870
4	1.6908	1.3428	1.3161	1.1395	1.1063	0.5845
5	1.5932	1.3636	1.2895	1.1832	1.2129	0.3803
H-L	0.4393	0.2217	-0.0607	-0.1640	-0.5724	

Panel B: 1964-1997

Ivol \ Mom	1	2	3	4	5	H-L
1	2.0964	1.6001	1.1929	0.9645	0.3999	1.6966
2	2.0492	1.5992	1.3195	1.1006	0.8159	1.2333
3	1.9530	1.4285	1.2200	1.1587	1.0013	0.9516
4	1.8754	1.4643	1.4261	1.2563	1.1151	0.7603
5	1.8384	1.5074	1.4242	1.3377	1.2908	0.5477
H-L	0.2580	0.0927	-0.2313	-0.3732	-0.8909	

Panel C: 1998-2013

Ivol \ Mom	1	2	3	4	5	H-L
1	1.8986	1.5541	1.3042	1.1337	1.1444	0.7542
2	1.5438	1.4087	1.1575	1.0111	1.2163	0.3275
3	1.3736	1.0611	1.0901	1.0338	1.2406	0.1330
4	1.3042	1.0885	1.0859	0.8949	1.0880	0.2163
5	1.0797	1.0625	1.0076	0.8597	1.0499	0.0298
H-L	0.8189	0.4916	0.2966	0.2740	0.0946	

Table 15: T-statistics stock-screening ivol

The table reports t-statistics for differnece in means for respective hedge portfolios quintile. Equation 4 describes the procedure.

MomQuintile	1	2	3	4	5
1964-2013	3.116	1.641	0.449	1.162	3.686
1964-1997	1.518	0.571	1.434	2.223	4.940
1998-2013	3.280	2.941	1.750	1.543	0.468

Table 16: Screening for profitability

The table reports descriptives for porfolios when screening for gross profitability. For each period considered the stock universe is first narrowed down such that topp 50 percent, 25 percent respective 10 percent are choosen accoring to profitability. Then within this selected universe topp 20 percent of the stocks are choosen accoring to the 12-month-1-month momentum measure. In order to make the outcome comparable one portfolio is created where topp 20 percent based on momentum is selected directly. The portfolios are monthly rebalanced.

Panel A: 1963-1997

Top % GP	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
Full	1.9151	6.0323	-0.7137	6.3354	44.0043	0.2645	1.9041
50%	1.9999	6.2833	-0.6688	5.7940	43.3754	0.2734	1.9886
25%	2.0992	6.2888	-0.6219	5.7458	43.1470	0.2783	2.0876
10%	2.2011	6.3169	-0.5328	5.4198	43.1617	0.2871	2.1891

Panel B: 1998-2013

Top % GP	Mean	Std	Skewness	Kurtosis	MaxDD	Turnover	MeanTC
Full	1.4379	6.5287	-0.1978	5.2876	37.2432	0.2697	4.9422
50%	1.6331	6.9128	-0.2347	4.9148	38.1044	0.2807	1.6214
25%	1.5913	6.9412	-0.1968	4.9084	37.2794	0.2882	1.5793
10%	1.7424	6.9035	-0.2590	4.6012	38.1495	0.3007	1.7299