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Industry Anomalies

An examination of asset pricing anomalies through an industry-specific framework

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Abstract:

The finance literature has discovered a large number of anomalies in the cross-section of stock returns over the past three decades. This thesis examines whether some of the most robust anomalies also appear within industries, and whether some are more prominent than others within specific industry sectors. We construct Fama-French type industry portfolios sorted on variables which have historically provided for higher expected returns in the aggregate market data: size, value, operating profitability, investment and momentum. We find comprehensive evidence that patterns of anomalous average returns observed in the U.S. stocks at large persist within industry subsets of the market, and that they exhibit differing premiums across industry sectors. We also find that industry-specific anomaly-based trading strategies can be formed in a way that delivers risk-adjusted outperformance over the historical market premium, but that said strategies tend to also be largely explained by the aggregate Fama-French risk factors. Lastly, we provide evidence that the industry-specific anomalous premiums vary across different time samples and put forward a case for further research on their persistence and predictability, as well as on optimal holding periods of their respective trading strategies.

Keywords: *Industry returns, Asset pricing, Anomalies, Industry Factors, Investment strategies*

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1 Introduction

Despite its popular practical application, industry-specific approach to investing and explaining expected stock returns has received substantially less academic attention. While there have been important contributions in the field of asset pricing of industries' costs of equity, little research has been done on the performance evaluation of industry-specific factor investing strategies. In this paper, we analyze the performance of zero-cost portfolios formed using the well-known methodologies of Fama-French five factor construction and Carhart's momentum within the industry-specific subsets of aggregate market data. Our main research question is:

Do the patterns of average returns formed on industry-specific factor portfolio sorts deviate from the well-established patterns observed in the entire market?

If this is the case, our follow up research question is:

To what extent can positive risk-adjusted performance be achieved that exploits the potentially higher presence of anomalous premiums in the industry-specific factor portfolios?

We thus closely examine the average return dispersion of industry portfolios sorted on variables which have historically provided for higher expected returns in the aggregate market data: size, value, operating profitability, investment and momentum. We examine the presence of such premiums and evaluate whether they offer comparatively better risk-adjusted performance than the aggregate market risk factors. We further examine how the average returns of such strategies perform across different time periods, in order to establish the level of robustness of anomaly presence within industries and if unexplained premiums can still be earned by industry-focused factor investors in recent time horizons. Lastly, we carefully examine the covariations of different factor-mimicking portfolios within each industry to find out whether different long-short portfolios yield significant premiums due to their similar underlying risk exposure.

The benefit of this research is twofold. Firstly, it offers a comprehensive examination of the returns of industry portfolios sorted on well-known Fama-French and Carhart variables, some of which have not been previously studied in the literature through an industry-specific framework. Secondly, it offers practical insight into which industry groups show higher anomalous returns over the observed time period, highlighting the potential benefits of adopting an industry focus in real-life factor trade implementation.

We find several anomaly-based industry strategies that yield returns not captured by the market premium over our sample period (1963-2019), as well as statistically significant risk-adjusted performance of combined industry factor strategies, both with respect to the market and with respect to the aggregate factors. We confirm the presence of industry momentum as an intra-industry phenomenon postulated by Moskowitz and Grinblatt (1999), whereby industry-grouped momentum stocks show significant unexplained average returns with respect to the market. However, we also find that only a few of such industry-grouped momentum trades outperform the individual stock momentum strategy formed on the aggregate market data. We do not find *systemic* presence of abnormal risk-adjusted returns in the industry-grouped cross-sectional dispersion of historical average returns of the Fama-French factors in our study, notably: size, value, operating profitability, and investment. Nonetheless, we highlight the importance of industry disaggregation for different factor investing strategies and how industry groups can be used to form profitable combined industry factor trades. Lastly, we show evidence of shared risk exposures for some of the industry-formed factor portfolios, noting the importance of careful selection of desired investing styles for investors focused only on specific industries.

2 Literature Review

2.1 Review of asset pricing models

In an attempt to determine how stock prices are formed in the financial markets and whether their returns exhibit predictability, academic research has produced numerous asset pricing models. The most well-known model in the finance literature and the most practically applied (see Welch (2008), Graham and Harvey (2000)) is the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965), on the basis of mean-variance portfolio theory postulated by Markowitz (1952). In the CAPM framework the expected return of a stock *i*, and equivalently its cost of equity, is described as:

$$\mathrm{E}(R_i) = R_f + \beta_i[\mathrm{E}(R_m) - R_f]$$

In the above equation, beta is obtained from a time-series regression of an individual stock return on the market return, net of risk-free rate. While the early empirical tests of CAPM confirmed the model's predictions (Black, Jensen and Scholes (1972), Fama and Macbeth (1973)), in more recent academic research CAPM has been oft-disproved due to its poor empirical track record. Friend and Blume (1970) provide some early doubt on the utility of CAPM theory in explaining market behavior, but it was not until Banz's (1981) research on the importance of companies' size in explaining asset prices and Fama and French (1992)'s evidence of flat relation between the market beta and average returns when not accounting for size, that this asset pricing model was seriously challenged. Numerous other papers question the validity of the early empirical tests (see Roll (1977), Kandel and Stambaugh (1995), Jagannathan and Wang (1996)).

Based on their aforementioned findings, Fama and French (1993) provide a revised asset pricing model that in addition to CAPM-implied market factor accounts for two additional risk factors: size, as defined by the companies' market capitalization, and value, defined by the ratio of companies' book value of equity to its market capitalization. They thus postulate a three-factor asset pricing model (FF3):

$$\mathrm{E}(R_i) = R_f + b_i\left[\mathrm{E}(R_m) - R_f\right] + s_i\mathrm{E}(SMB) + h_i\mathrm{E}(HML)$$

In the above equation, SMB represents the return on a diversified portfolio of small-cap stocks less a diversified portfolio of large-cap stocks. HML is the difference between a diversified portfolio of stocks with high book equity to market equity (B/M) and low book-to-market equity. Fama and French conclude that the three-factor model captures the variation in expected returns of stocks and portfolios *i* significantly better than the CAPM. Considering that the two new seemingly priced factors are not explained by the CAPM framework, these risk factors were labeled "anomalies", often referred to as size and value effects in the academic literature. Since the introduction of FF3, size effect has proved to be less persistent than the value effect, with Horowitz (2000) evidencing that it is not present since the 1980s, and Van Dijk (2011) showcasing that its significance varies over time.

The FF3 asset pricing model was further extended by Carhart's (1997) research on the "momentum" effect, which provided significant explanatory power on the persistence in equity mutual funds' mean and risk-adjusted returns. The Fama-French-Carhart (FFC4) four-factor asset pricing model, as it became known, took on the following form:

$$\mathrm{E}(R_i) = R_f + b_i\left[\mathrm{E}(R_m) - R_f\right] + s_i\mathrm{E}(SMB) + h_i\mathrm{E}(HML) + m_i\mathrm{E}(PR1YR)$$

In the above equation, the newly added PR1YR factor is constructed from the returns of a value-weighted, zero-investment portfolio for one-year momentum in the aggregate stock returns. The FF3 and Carhart asset pricing models proved rather successful in explaining the drivers of asset returns and thus became a staple in the academic asset pricing literature, as well as practical risk-adjusted performance evaluation of portfolio managers and their investment strategies.

Recently, however, Fama and French (2015) further extended their FF3 model by adding two new risk factors: investment and profitability. This was motivated by significant literature pointing towards firms' profitability and investment variables adding to the explanatory power of aggregate stock returns in the market. The Fama-French five-factor (FF5) asset pricing model can be described with the following equation:

$$\mathrm{E}(R_i) = R_f + b_i\left[\mathrm{E}(R_m) - R_f\right] + s_i\mathrm{E}(SMB) + h_i\mathrm{E}(HML) + r_i\mathrm{E}(RMW) + c_i\mathrm{E}(CMA)$$

The new RMW (robust minus weak) factor in their model, is formed as a difference between diversified portfolios of stocks sorted on their level of operating profitability, 'robust' implying firms with good operating profitability and 'weak' implying firms with poor operating profitability. The CMA (conservative minus aggressive) factor, on the other hand, is formed as a difference between diversified portfolios of stocks sorted on their level of capital investments, as proxied by their growth in total assets; 'conservative' implying low levels of firm's total asset growth and 'aggressive' implying high levels of growth in total assets over a one year period. Interestingly, Fama and French find that once the operating profitability and investment levels of the firms are accounted for, the HML factor becomes redundant in the explanation of the cross-sectional dispersion of historical average stock returns.

The success of the aforementioned Fama-French and Carhart asset pricing models in explaining the drivers of the abnormal average returns not captured by CAPM made their use widespread in the academia. However, the lack of proven theoretical explanations for why these risk factors do so well in explaining stock returns also made them known as asset pricing "anomalies". Having reviewed the well-known asset pricing models that led to the popularization of said anomalies, we next turn to defining what these anomalies actually are and what do they imply.

2.2 Defining anomalies

Banz (1981) first provided evidence on the importance of the "size" anomaly, whereby small-cap stocks yielded abnormally higher average returns compared to the large-cap stocks and the market. Numerous research followed on the evidence of the so-called "value" anomaly, where high book-to-market stocks, as defined by their book equity and market capitalization, exhibited persistently higher average returns (see Stattman (1980), Basu (1983), Rosenberg, Reid, and Lanstein (1985); Chan, Hamao and Lakonishok (1991)). Carhart (1997), as previously mentioned, provides strong evidence of the explanatory power of the "momentum" anomaly, by demonstrating that Hendricks, Patel and Zeckhauser's (1993) "hot-hands" phenomenon is explained by the one-year momentum effect postulated by Jegadeesh and Titman (1993), whereby portfolios formed by buying stocks that have generated high returns and selling stocks with low returns over a three to twelve month holding periods yield significant positive returns. Haugen and Baker (1996) and Cohen, Gompers, and Vuolteenaho (2002) provide evidence that firms with higher profitability generate higher average returns, which is later strongly confirmed by Novy-Marx (2013), evidencing the "profitability" anomaly. Fairfield, Whisenant, and Yohn (2003) and Titman, Wei and Xie (2004) also find that companies which substantially increase their capital investments subsequently achieve lower average returns, establishing the so-called "investment" anomaly. Green, Hand and Zhang (2013) further aggregate more than 300 characteristic-based anomalies that predict cross-sectional returns, many of which seem to have disappeared following their publication (McLean and Pontiff, 2016) or proved redundant (Feng, Giglio, Ziu, 2020). We thus focus our research on few of the most persistent anomalies within academia, those with strong evidence of explaining stock returns through their respective asset pricing models, and those that thereby have the largest chance of being practically implemented by factor style investors. These are: size, value, momentum, profitability and investment.

2.3 Industry anomalies

Albeit many studies have examined the persistence of anomalies in country-specific and global contexts (Griffin, 2002), few have focused on determining the performance of industry-specific portfolios of stocks. As industries are, in theory, affected by common within-industry characteristics which are not necessarily relevant across industries, one might expect that they showcase different results when tested against the same anomaly-based investment strategy.

Indeed, the asset pricing literature does provide evidence of the importance of industry-based perspective on the aggregate stock price formation. Fama and French (1997) find that industry costs of equity are difficult to price through both generalized CAPM and FF3 framework, a finding that is later supported by Vliet and Post (2004). Chou, Ho & Ko (2012) further confirm that industry-sorted stocks cannot be fully explained by standard asset pricing models, nor by the extracted factors from asymptotic principal component analyses. Lewellen, Nagel and Shanken (2010) provide evidence that risk-based asset pricing models fail to explain the cross-section of returns on industry portfolios. This shows that the standard asset pricing models tend to poorly explain industry returns, implying that industry-specific return dynamics might significantly differ from the evidenced asset price formation observed in the aggregate market. The explanatory power is somewhat improved, however, once one accounts for industry-specific risk factors. Cavaglia, Brightman and Aked (2000), for example, find that the returns of national industry portfolios are better explained by industry-specific factors rather than country-specific factors. Moerman (2005) applies an industry-specific asset pricing model using the FF3 framework on the European data and finds that the industry-specific asset pricing model performs better than the aggregate euro-area model in explaining the cross-section of stock returns. Thus, evidence suggests that industry disaggregation of the aggregate market sample matters, which further implies that the presence of anomalies might also differ across industries, leaving potentially unexplained premiums to be earned through industry-specific anomaly-based investment styles.

2.4 Anomaly-based investment styles

The academic appreciation of industry effects for asset pricing models spurred some interest in the analysis of the performance of industry-based style investment strategies. Capaul (1999) assesses the performance of anomaly-based investment styles in industry-sorted global portfolios and finds evidence of above-average returns in the equal-weighted industry portfolios formed on size, value and momentum anomalies. His research documents differing average return premiums across industries, but also points towards low levels of statistical significance and is rather restricted on the time period used, namely January 1991 to August 1998. Moreover, Moskowitz and Grinblatt (1999) demonstrate that "industry momentum" portfolios formed by buying stocks from past winning industries and selling stocks of past losing industries lead to higher returns, even after controlling for size, value and individual stock momentum factors. This leaves the question of how well the other factors, especially those more recently discovered, would perform when implemented as trading strategies within industry subsets of aggregate market data, and to what extent is it possible to generate above-average risk adjusted returns by pursuing industry-specific factor investing styles.

This thesis, motivated by Capaul's (1999) and Moskowitz-Grinblatt's (1999) research, examines the industry effects of the five well-known anomalies using the Fama-French methodology. It adds to the literature in three main ways. Firstly, it examines the data across a larger time horizon than Capaul (1999) using a different methodology, determining whether unexplained within-industry return patterns persist when applied over a longer timeframe. Secondly, it tests the performance of strategies formed on a completely new set of variables, namely the Fama-French operating profitability and investment factors, which to our knowledge has not been previously performed. Lastly, based off of Griffin's (2002) research that factor portfolios constructed from local firms generally perform better than factor portfolios formed using global data, we additionally test whether Capaul's (1999) inferences perform comparatively better when observed through a local, country-based rather than global industry dataset. The thesis also provides important evidence of the importance of industry selection for the formation of factor investing strategies, whereby addition or exclusion of certain industry groups allows for above-average returns that outperform the factor strategies constructed on the aggregate market sample.

3 Methodology

In order to test the within-industry effects of common asset pricing anomalies, we adopt the Fama-French methodology of portfolio sorting and factor construction, which is a widespread academic standard. The overview of data, variables and methodology we use in the analysis is presented in further detail in the following subheadings.

3.1 Data

The primary data used for the analysis is sourced from the Center for Research in Security Prices (CRSP) using the Wharton Data Research Services (WRDS) database. The database consists of monthly returns for all U.S. companies listed on NASDAQ, AMEX and NYSE stock exchanges in the period 1926 to 2019. We also download the annual and quarterly income statement and balance sheet data from COMPUSTAT, primarily for the purpose of accounting measures used for the construction of some of the factors. The accounting data from COMPUSTAT is restricted to the period 1951 to 2019. We also obtain the Davis Book Equity data from Kenneth French's website following Fama-French methodology descriptions. We then merge the datasets using their linked PERMNOs (company identifiers) to match them with the CRSP data. The data for our risk-free rate (one-month U.S. Treasury Bill), and aggregate risk factors used for comparison of various portfolio performances are also downloaded from Kenneth French's website. The data is filtered to include only companies with CRSP share codes of 10 and 11, to ensure Market Equity calculations are based on ordinary common shares, with ADRs excluded, of companies registered in the United States; as well as to ensure funds, trusts and REITs are eliminated from the data sample. The data is also filtered to exclude companies with negative book equity. Even though our initial dataset begins in 1926, for most of the calculations the sample is restricted to the time periods where sufficient data is available for all variables needed for our calculations and for their respective factor formation. The initial dataset consists of 3,593,158 observations, including 24,991 companies. The main dataset we use for the analysis (June 1963 – June 2019) consists of 3,177,931 observations, including 24,321 unique companies across the time period.

3.2 Defining industries

In order to form industry-based portfolios, we first need to define a criteria for the industry-level groupings. Ideally, we want to form sub-portfolios on the presumption of within-industry homogeneity of groups of companies, be it in terms of similarity of their products and services or the way their prices respond to market-wide and industry-specific information. While Bhojraj, Lee and Oler (2003) provide a critical view of the established industry classifications standards used for academic research; Chan, Lakonishok and Swaminathan (2007) conclude that the Fama-French industry aggregations yield similar, albeit imperfect, levels of within-group average return correlations across large-cap, small-cap and operating performance categories, when compared to the Global Industry Classification System (GICS). We thus settle for the academic standard used by Fama and French (1997), the four-digit Standard Industrial Classification (SIC) code groupings, acknowledging its drawbacks and the implicitly broad attributes they assign to the selected industry classes. We also decide to work with a sample of 12 industry groups, in order to have sufficient number of companies for within-industry portfolio construction for as long of a timeframe as possible. Not having enough companies for appropriate per-industry portfolio sorting, and subsequent factor construction, is undesirable as our factors are formed to mimic long-short self-financing portfolios, which is unrealistic to do with only a few companies. Hence, while somewhat arbitrary, the use of 12 industry groups ensures a compromise between the appropriate level of industry disaggregation and the realistic application of potential industry-based factor trades.

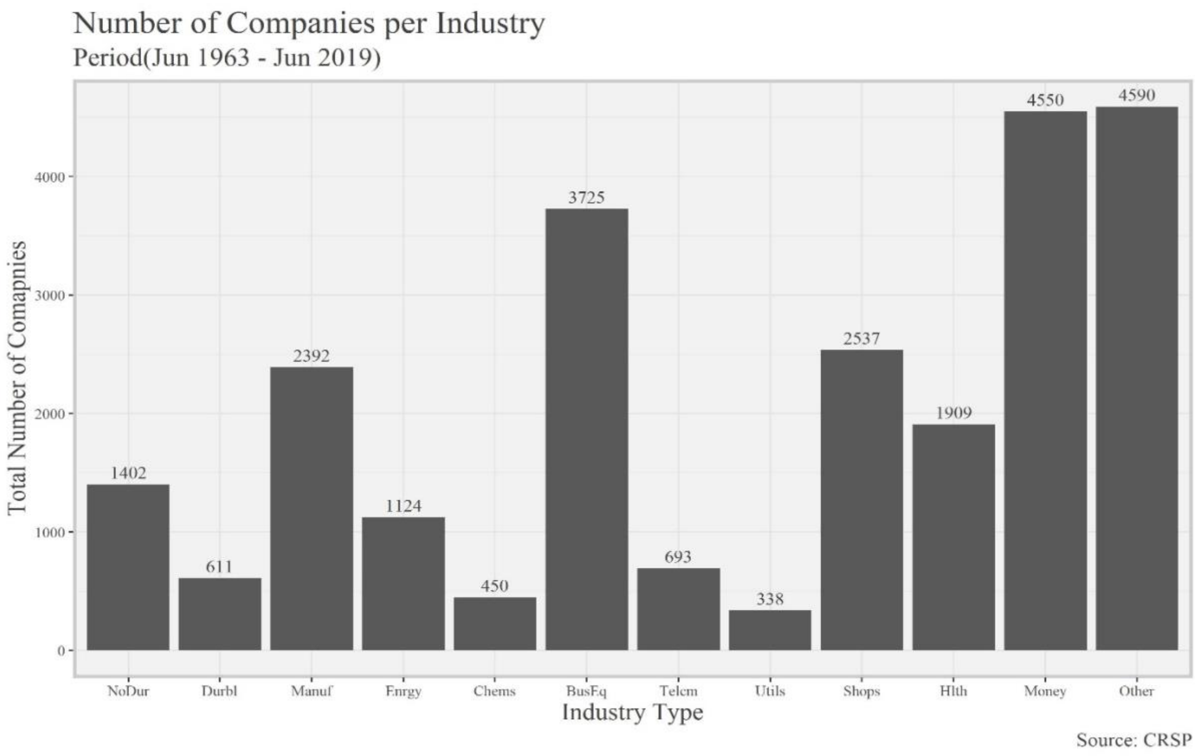
Table 1: Industry Classifications

	Industry Name:	SIC code ranges:
1.	<u>Consumer Nondurables</u>: *Food, Tobacco, Textiles, Apparel, Leather, Toys*	0100-0999; 2000-2399; 2700-2749; 2770-2799; 3100-3199; 3940-3989.
2.	<u>Consumer Durables:</u> *Cars, TVs, Furniture, Household Appliances*	2500-2519; 2590-2599; 3630-3659; 3710-3711; 3714-3714; 3716-3716; 3750-3751; 3792-3792; 3900-3939; 3990-3999.
3.	<u>Manufacturing:</u> *Machinery, Trucks, Planes, Office Furniture, Paper, Com Printing*	2520-2589; 2600-2699; 2750-2769; 3000-3099; 3200-3569; 2600-2699; 2750-2769; 3000-3099; 3200-3569; 3580-3629; 3700-3709; 3712-3713; 3715-3715; 3717-3749; 3752-3791; 3793-3799; 3830-3839; 3860-3899.
4.	<u>Energy:</u> *Oil, Gas, and Coal Extraction and Products*	1200-1399; 2900-2999.
5.	<u>Chemicals:</u> *Chemicals and Allied Products*	2800-2829; 2840-2899.

6. <u>Business Equipment:</u> *Computers, Software, and Electronic Equipment*	3570-3579; 3660-3692; 3694-3699; 3810-3829; 7370-7379.
7. <u>Telecoms:</u> *Telephone and Television Transmission*	4800-4899.
8. <u>Utilities:</u>	4900-4949.
9. <u>Shops:</u> *Wholesale, Retail, and Some Services (Laundries, Repair Shops)*	5000-5999; 7200-7299; 7600-7699.
10. <u>Healthcare:</u> *Healthcare, Medical Equipment, and Drugs*	2830-2839; 3693-3693; 3840-3859; 8000-8099.
11. <u>Money:</u> *Financial Institutions*	6000-6999.
12. <u>Other:</u> *Mines, Construction, Building Materials, Transportation, Hotels, Business Services, Entertainment*	All other code ranges not exhibited above.

Once companies are sorted in their respective industry groups, our dataset consists of the following number of companies presented in the Graph 3.2.1 below:

Graph 3.2.1: Unique companies within selected industry groups.



Moreover, the descriptive statistics of our industry groupings are presented in the Table 3.2.1 below. Full yearly time series of number of companies per industries are further presented in Appendix A.

Table 3.2.1: Industry Statistics. Average, Min and Max describe the number of companies over the sample time period (June 1963 – June 2019) and respectively the Annualized Returns, Standard Deviations and Sharpe Ratios cover the return statistics for value-weighted returns.

Industry	Average	Min	Max	Annual Ret (%)	Standard Dev (%)	Sharpe Ratio
NoDur	330	137	609	7.00	14.84	0.47
Durbl	144	68	226	2.46	22.38	0.11
Manuf	625	269	1001	4.78	18.37	0.26
Enrgy	233	108	504	5.28	18.88	0.28
Chems	119	70	159	5.41	16.01	0.34
BusEq	745	130	1598	5.67	22.55	0.25
Telcm	117	25	261	4.23	15.78	0.27
Utils	153	76	208	4.23	13.95	0.30
Shops	549	219	932	5.84	16.91	0.35
Hlth	396	39	819	6.85	16.49	0.42
Money	913	142	1507	5.39	18.59	0.29
Other	735	247	1291	4.49	19.23	0.23

We test the final dataset against the Fama-French 12 industry returns posted on Kenneth French's website. We do this by calculating equal-weighted and value-weighted return time-series of all the companies in our respective industry groups. We obtain return correlations of more than 98%, and in most cases more than 99%, of our industry group returns compared to the published Fama-French data. We also check the mean returns of each industry across the 56 year sample of monthly returns and find very little difference to the Fama-French returns, with the largest mean differential being 8 basis points for the Durables industry group. The summary of our sample data comparison with the published Fama-French industry returns data can be found in Appendix B. This process reassures us that the data sample we are observing is close to the data used by Fama-French in their factor construction process, which provides for consistency and more legitimate comparison of industry-specific portfolios with the aggregate data portfolios further on in our analysis.

3.3 Defining variables

As previously mentioned, in order to follow Fama-French methodology of portfolio sorting and factor construction, we first need to define the main variables used for this process. All of the variables are either directly imported from the data sources described above or, where needed, calculated using the rest of the imported data for each company. In our definitions of variables below, we try to deviate from the Fama-French and Carhart definitions as little as possible.

Book Equity (B), from hereon also referred to as "book value", is defined as the book value of shareholder equity (total assets minus total liabilities), plus balance-sheet deferred taxes and investment tax credit (where available), less the book value of preferred stock.

Market Equity (M), or equivalently market capitalization, is defined as the stock price times the number of ordinary common shares outstanding. We use this variable to define the "size" of companies in the later portfolio sorts.

Book-to-market ratio (B/M) is defined as book equity divided by market equity. We use this variable to define the "value" parameter of companies in the portfolio sorting procedure. Following Fama-French, the B/M ratio used for the formation of portfolios in June of year t is the book equity of a company for the previous fiscal year-end (t-1), divided by the market capitalization of the company at the end of December of t-1. The reasoning behind the six month gap is to have a more realistic portfolio construction process, as most companies only publish their annual reports three or more months after the end of the fiscal year.

Operating Profitability (OP) is defined as annual revenues less cost of goods sold, interest expenses and selling, general and administrative expenses; divided by book equity (B). The income statement data for this variable is sourced from COMPUSTAT.

Investment (INV) is defined as the return on total assets of a company. For portfolios formed in June of year t, it represents the ratio of the company's total assets in fiscal year-end t-1, less total assets in t-2, divided by the total assets in t-2. Where end-of-year total assets in t-2 are not available, the variable is defined as the asset change between total assets in t-1 and the nearest historical fiscal year-end.

Momentum (MOM) spread in each month is defined as the cumulative return of a stock in the past 12 months, lagged by one month. Thus, for a stock in June of year t, the momentum spread is the cumulative monthly return the stock has achieved from its price in May of year t-1 to its price in May of year t.

3.4 Construction of portfolios

Following the methodology of Fama and French (1992), we first construct portfolios by sorting companies into different pre-defined sets, based on variables defined above. The idea behind this is to capture and observe the patterns (and thereby effects) these variables have on the average monthly excess returns of companies grouped into their respective characteristic-based sub-portfolios. We use the unconditional (independent) portfolio sorting methodology, which is the academic standard, as it allows us to group companies into sub-portfolios independently of the variable the company is sorted on. In conditional multi-variate sorting procedure, the company is first grouped into sub-portfolios based on the first variable, and then within the constructed sub-portfolio group it is sorted on the next variable. This gives significantly more weight to the first sorting factor, which would require us to define which anomalies are more important ex-ante and thereby might lead to misleading conclusions about the average return patterns. The unconditional sorting procedure, on the other hand, allows us to generate intersections of stocks after they have been sorted on each of the dimensions with the same breakpoint characteristics, making the order of the sorting independent of the supposed ex-ante importance of variables used. The drawback of this method is that for some of the sub-portfolios, especially in the early periods of the analysis, the number of companies filled into each of the sub-portfolios can be low, leading to sub-portfolios that are not fully diversified.

We further use the value-weighted sorts, based on companies' market capitalization, as the value-weighted components approach captures the different return behaviors of characteristic-based portfolios in a way that corresponds to more realistic investment opportunities (Fama and French, 1992). We split the portfolios into halves, terciles and quintiles per relevant variable for all companies, but using only the NYSE-listed companies' market capitalization breakpoints (Fama and French 1993, 2015). Considering all of our bivariate sorts are first formed on "size", as defined by market equity, the NYSE breakpoint condition is relevant to remain consistent across all sorts in our analysis, even when the second sorting variable does not require market capitalization weighting (e.g. momentum, investment and profitability).

The portfolio sorting procedure is explained in detail in the Table 3.4.1 below. The choice of breakpoints, hence the number of sub-portfolios created, is still perceived as somewhat arbitrary in the academic literature, so we follow the academic standard of 2x3 portfolio sorts proposed by Fama and French, ensuring consistent comparisons of within-industry and across-industry effects. Stocks are assigned to their respective portfolios at the end of June of year t, based on the aforementioned independent sort procedure, and are rebalanced yearly.

Table 3.4.1: Portfolio formation

Type of sort:	Portfolio variables:	Breakpoints (NYSE only):
Bivariate: 2x3	6 portfolios on *Size* and *B/M* 6 portfolios on *Size* and *OP* 6 portfolios on *Size* and *INV* 6 portfolios on *Size* and *MOM*	*Size*: Median *B/M*: 30th and 70th percentile *OP*: 30th and 70th percentile *INV*: 30th and 70th percentile *MOM*: 30th and 70th percentile

We also perform the 5x5 independent sorts and report our results in Appendix F, to provide a more detailed and granulated depiction of the impact each variable has on the average returns per industry, if and when the 25 sub-portfolios are able to be formed. However, the average premiums from this sorting procedure should be interpreted with caution as the return time-series are not always fully continuous across all of the sub-portfolios, with some of the extreme-end portfolios occasionally being empty in the early time periods of the analysis.

3.5 Factor definitions

Having formed the sub-portfolios using the methodology described above, we construct the factor-mimicking, long-short, self-financing portfolios based on the pre-defined anomaly variables. Our factors are formed by taking the average of the top and bottom terciles or halves and subtracting one average from the other. Below we present an example of a bivariate 2x3 sorts which produces 6 sub-portfolios, sorted on *Size* and *Book-to-Market.*

Book-to-Market (B/M)

Size (M)			
	Small.Low	*Small.Neutral*	*Small.High*
	Big.Low	*Big.Neutral*	*Big.High*

In the example above, the "extremes" used for factor construction of the *Size* (SMB) anomaly are the top and bottom row; whereas the portfolios used for factor construction of the *Value* (HML) anomaly are the first and last column. In order to form the SMB factor from a 2x3 portfolio sorts, we use the following formula:

$$HML = \frac{(Small.High + Big.High)}{2} - \frac{(Small.Low + Big.Low)}{2}$$

Thus, the SMB factor is simply the difference each month between the average return of 3 small portfolios and average return of 3 big portfolios, as defined by their market equity and using the NYSE breakpoints described in the previous section. The value (HML) factor is the difference each month between the average return of 2 portfolios with high book-to-market and the average return of the 2 portfolios with low book-to-market ratios. The same process is repeated with other variables (operating profitability, investment and momentum). Considering that we use Size (market equity) as a first sorting variable in all of our bivariate sorts, the rest of the factors are formed in the same manner as value (HML) described above, with the only difference being the variable we use instead of book-to-market ratio (B/M). Therefore, we arrive to a total 5 factor-mimicking portfolios based on asset-pricing anomalies: SMB (Small minus Big, using market equity variable), HML (High minus Low, using book-to-market ratio), RMW (Robust minus Weak, using operating profitability variable), CMA (Conservative minus Aggressive, using investment variable), and UMD (Up minus Down, using the momentum variable). The end products of the factor construction are the monthly return time-series that mimic anomaly-based, long-short investment strategies. Considering that we are interested in analyzing the within-industry effects and performance of these strategies, we apply the said methodology for each of the 12 predefined industries, arriving to a total of 60 monthly return time-series. As a benchmark for our analysis, we use the monthly value-weighted excess market return imported from Kenneth French's website, as well as the aggregate Fama-French factors' monthly time series. The summary of our sample data comparison with the published Fama-French factor returns data can be found in Appendix B.

3.6 Performance evaluation

Once we have the industry-specific factor-mimicking time series constructed, we proceed to analyze their risk-adjusted performance compared to the market and compared to their respective factor strategies formed using the aggregate data sample. We first conduct a series of regressions of industry-specific factor portfolios on the excess market returns, in search of a statistically significant 'Jensen's alpha' per industry. We then turn to a series of regressions of industry-specific factor portfolios on their respective aggregate risk factors, in order to see if certain industry portfolios remain unexplained by the aggregate factor strategy, thereby offering within-industry anomalous premiums. Next, we evaluate the risk-adjusted performance of selected combined industry strategies, to test the performance of anomaly-based strategies formed using only industries that exhibit strong results in the previous two sets of regressions. The aim here is to evaluate how a portfolio of top-performing industries performs in terms of alpha and its exhibited volatility, compared to the single-industry portfolios. We then check for robustness of the results over different time periods. Lastly, we finalize the analysis by conducting a series of spanning regressions of the industry portfolios, where we regress each of the industry factor portfolios on all of the other factor portfolios, in order to determine to what extent the industry-specific factors comove – and whether they thereby potentially offer the same type of risk exposure for an investor interested in a specific industry.

4 Empirical Results

4.1 Patterns of Average Returns

We start the analysis by observing the patterns of average portfolio returns formed as intersections of two size groups and three book-to-market, operating profitability, investment and momentum groups for each of the industries. We are interested in finding out whether the return patterns differ across industries, and to what extent they differ compared to the average returns of 6 sub-portfolios on aggregate data, as performed by Fama and French (2015). For the profitability and investment sorts, we do not report the results for the industry group 11 ("Money"), as the accounting standards are different for many of the financial institutions – thereby potentially producing misleading results if our variable definitions for investment and profitability are applied. We present the findings on the following pages.

Table 4.1.1: Average monthly gross returns (%) for industry portfolios formed on Size and Value (B/M), 1963-2019.

1. Non-Durables

	Low	Neutral	High	Avg.
Small	0.76	1.10	1.17	**1.01**
Big	0.98	1.22	1.27	**1.16**
Avg.	**0.87**	**1.16**	**1.22**	
Avg HML				**0.36**
Avg SMB				**-0.15**

2. Durables

	Low	Neutral	High	Avg.
Small	0.80	1.10	1.28	**1.06**
Big	0.58	1.14	0.82	**0.85**
Avg.	**0.69**	**1.12**	**1.05**	
Avg HML				**0.36**
Avg SMB				**0.21**

3. Manufacturing

	Low	Neutral	High	Avg.
Small	0.85	1.23	1.31	**1.13**
Big	0.92	0.92	1.12	**0.99**
Avg.	**0.89**	**1.07**	**1.22**	
Avg HML				**0.33**
Avg SMB				**0.14**

4. Energy

	Low	Neutral	High	Avg.
Small	0.67	1.04	1.26	**0.99**
Big	0.59	1.10	1.16	**0.95**
Avg.	**0.63**	**1.07**	**1.21**	
Avg HML				**0.58**
Avg SMB				**0.04**

5. Chemicals

	Low	Neutral	High	Avg.
Small	1.02	1.30	1.32	**1.21**
Big	0.74	1.03	1.27	**1.01**
Avg.	**0.88**	**1.17**	**1.29**	
Avg HML				**0.41**
Avg SMB				**0.20**

6. Business Equipment

	Low	Neutral	High	Avg.
Small	0.80	1.21	1.58	**1.20**
Big	1.15	1.08	1.32	**1.18**
Avg.	**0.97**	**1.14**	**1.45**	
Avg HML				**0.47**
Avg SMB				**0.01**

7. Telecoms

	Low	Neutral	High	Avg.
Small	1.08	1.13	1.15	**1.12**
Big	0.91	0.62	1.01	**0.85**
Avg.	**0.99**	**0.88**	**1.08**	
Avg HML				**0.09**
Avg SMB				**0.27**

8. Utilities

	Low	Neutral	High	Avg.
Small	0.88	1.03	1.10	**1.00**
Big	0.60	0.87	0.97	**0.81**
Avg.	**0.74**	**0.95**	**1.04**	
Avg HML				**0.30**
Avg SMB				**0.19**

9. Shops

	Low	Neutral	High	Avg.
Small	1.04	1.04	1.19	**1.09**
Big	1.00	0.99	1.02	**1.00**
Avg.	**1.02**	**1.01**	**1.11**	
Avg HML				**0.09**
Avg SMB				**0.09**

10. Healthcare

	Low	Neutral	High	Avg.
Small	0.94	1.41	1.54	**1.30**
Big	1.06	1.04	1.23	**1.11**
Avg.	**1.00**	**1.22**	**1.39**	
Avg HML				**0.38**
Avg SMB				**0.18**

11. Money

	Low	Neutral	High	Avg.
Small	0.96	1.11	1.30	**1.12**
Big	1.01	0.93	1.15	**1.03**
Avg.	**0.98**	**1.02**	**1.22**	
Avg HML				**0.24**
Avg SMB				**0.09**

12. Other

	Low	Neutral	High	Avg.
Small	0.85	1.24	1.14	**1.08**
Big	0.78	1.05	0.99	**0.94**
Avg.	**0.81**	**1.15**	**1.07**	
Avg HML				**0.25**
Avg SMB				**0.14**

Table 4.1.2: Average monthly gross returns (%) for industry portfolios formed on Size and Profitability, 1963-2019.

1. Non-Durables

	Weak	Neutral	Robust	Avg.
Small	0.86	1.15	1.24	**1.08**
Big	0.97	1.01	1.11	**1.03**
Avg.	**0.92**	**1.08**	**1.18**	
Av RMW				**0.26**
Av SMB				**0.05**

2. Durables

	Weak	Neutral	Robust	Avg.
Small	0.97	1.19	1.20	**1.12**
Big	0.66	0.88	0.82	**0.79**
Avg.	**0.81**	**1.04**	**1.01**	
Av RMW				**0.19**
Avg SMB				**0.34**

3. Manufacturing

	Weak	Neutral	Robust	Avg.
Small	1.05	1.23	1.23	**1.17**
Big	0.69	0.97	0.94	**0.87**
Avg.	**0.87**	**1.10**	**1.09**	
Av RMW				**0.22**
Avg SMB				**0.30**

4. Energy

	Weak	Neutral	Robust	Avg.
Small	0.71	1.11	1.06	**0.96**
Big	0.93	0.98	1.00	**0.97**
Avg.	**0.82**	**1.04**	**1.03**	
Av RMW				**0.21**
Avg SMB				**-0.01**

5. Chemicals

	Weak	Neutral	Robust	Avg.
Small	1.11	1.25	1.36	**1.24**
Big	1.10	0.94	0.84	**0.96**
Avg.	**1.10**	**1.10**	**1.10**	
Av RMW				**0.00**
Avg SMB				**0.28**

6. Business Equipment

	Weak	Neutral	Robust	Avg.
Small	1.11	1.19	1.34	**1.21**
Big	0.99	1.06	1.14	**1.06**
Avg.	**1.05**	**1.12**	**1.24**	
Av RMW				**0.19**
Avg SMB				**0.15**

7. Telecoms

	Weak	Neutral	Robust	Avg.
Small	0.96	1.17	1.58	**1.24**
Big	0.91	0.75	0.96	**0.88**
Avg.	**0.94**	**0.96**	**1.27**	
Av RMW				**0.33**
Avg SMB				**0.36**

8. Utilities

	Weak	Neutral	Robust	Avg.
Small	0.85	0.98	1.10	**0.97**
Big	0.75	0.82	0.83	**0.80**
Avg.	**0.80**	**0.90**	**0.97**	
Av RMW				**0.17**
Avg SMB				**0.17**

9. Shops

	Weak	Neutral	Robust	Avg.
Small	0.89	1.16	1.17	**1.07**
Big	0.69	1.07	1.03	**0.93**
Avg.	**0.79**	**1.11**	**1.10**	
Av.RMW				**0.31**
Avg SMB				**0.14**

10. Healthcare

	Weak	Neutral	Robust	Avg.
Small	1.28	1.35	1.46	**1.36**
Big	1.20	0.91	1.10	**1.07**
Avg.	**1.24**	**1.13**	**1.28**	
Av RMW				**0.04**
Avg SMB				**0.29**

11. Money

	Weak	Neutral	Robust	Avg.
Small	-	-	-	-
Big	-	-	-	-
Avg.	**-**	**-**	**-**	
Av RMW				-
Avg SMB				-

12. Other

	Weak	Neutral	Robust	Avg.
Small	0.81	1.20	1.24	**1.08**
Big	0.98	0.88	0.89	**0.91**
Avg.	**0.89**	**1.04**	**1.06**	
Av.RMW				**0.17**
Avg SMB				**0.17**

Table 4.1.3: Average monthly gross returns (%) for industry portfolios formed on Size and Investment, 1963-2019.

1. Non-Durables

	Cons	Neutral	Aggr	Avg.
Small	0.99	1.20	0.85	**1.01**
Big	1.16	1.10	0.94	**1.07**
Avg.	**1.07**	**1.15**	**0.89**	
Av CMA				**0.18**
Avg SMB				**-0.05**

2. Durables

	Cons	Neutral	Aggr	Avg.
Small	1.30	1.20	0.87	**1.12**
Big	1.08	0.83	0.80	**0.90**
Avg.	**1.19**	**1.02**	**0.83**	
Av CMA				**0.36**
Avg SMB				**0.22**

3. Manufacturing

	Cons	Neutral	Aggr	Avg.
Small	1.26	1.21	0.99	**1.15**
Big	1.09	0.97	0.82	**0.96**
Avg.	**1.18**	**1.09**	**0.90**	
Av CMA				**0.27**
Avg SMB				**0.20**

4. Energy

	Cons	Neutral	Aggr	Avg.
Small	0.94	1.07	0.87	**0.96**
Big	0.88	1.04	0.92	**0.95**
Avg.	**0.91**	**1.05**	**0.90**	
Av CMA				**0.02**
Avg SMB				**0.01**

5. Chemicals

	Cons	Neutral	Aggr	Avg.
Small	1.32	1.19	0.93	**1.15**
Big	0.96	1.05	0.78	**0.93**
Avg.	**1.14**	**1.12**	**0.86**	
Av CMA				**0.28**
Avg SMB				**0.22**

6. Business Equipment

	Cons	Neutral	Aggr	Avg.
Small	1.46	1.39	0.86	**1.24**
Big	1.26	0.98	1.20	**1.15**
Avg.	**1.36**	**1.19**	**1.03**	
Av CMA				**0.33**
Avg SMB				**0.09**

7. Telecoms

	Cons	Neutral	Aggr	Avg.
Small	1.36	1.22	1.02	**1.20**
Big	0.74	0.83	0.94	**0.84**
Avg.	**1.05**	**1.02**	**0.98**	
Av CMA				**0.07**
Avg SMB				**0.36**

8. Utilities

	Cons	Neutral	Aggr	Avg.
Small	1.11	0.96	0.99	**1.02**
Big	0.93	0.85	0.66	**0.81**
Avg.	**1.02**	**0.91**	**0.82**	
Av CMA				**0.20**
Avg SMB				**0.21**

9. Shops

	Cons	Neutral	Aggr	Avg.
Small	1.16	1.23	0.98	**1.12**
Big	1.16	0.92	1.00	**1.03**
Avg.	**1.16**	**1.08**	**0.99**	
Av CMA				**0.17**
Avg SMB				**0.10**

10. Healthcare

	Cons	Neutral	Aggr	Avg.
Small	1.67	1.52	1.00	**1.40**
Big	1.14	1.10	0.94	**1.06**
Avg.	**1.40**	**1.31**	**0.97**	
Av CMA				**0.43**
Avg SMB				**0.34**

11. Money

	Cons	Neutral	Aggr	Avg.
Small	-	-	-	-
Big	-	-	-	-
Avg.	-	-	-	
Av CMA				-
Avg SMB				-

12. Other

	Cons	Neutral	Aggr	Avg.
Small	1.37	1.23	0.98	**1.19**
Big	1.14	1.05	0.68	**0.96**
Avg.	**1.26**	**1.14**	**0.83**	
Av CMA				**0.43**
Avg SMB				**0.23**

Table 4.1.4: Average monthly gross returns (%) for industry portfolios formed on Size and Momentum, 1963-2019.

1. Non-Durables

	Down	Neutral	Up	Avg.
Small	0.19	0.73	0.90	**0.61**
Big	0.47	0.60	0.87	**0.65**
Avg.	**0.33**	**0.66**	**0.89**	
Av UMD				**0.55**
Avg SMB				**-0.04**

2. Durables

	Down	Neutral	Up	Avg.
Small	0.34	0.83	0.95	**0.71**
Big	0.17	0.45	0.70	**0.44**
Avg.	**0.26**	**0.64**	**0.83**	
Av UMD				**0.57**
Avg SMB				**0.27**

3. Manufacturing

	Down	Neutral	Up	Avg.
Small	0.41	0.78	1.09	**0.76**
Big	0.26	0.53	0.73	**0.51**
Avg.	**0.33**	**0.66**	**0.91**	
Av UMD				**0.58**
Avg SMB				**0.25**

4. Energy

	Down	Neutral	Up	Avg.
Small	0.12	0.52	0.82	**0.49**
Big	0.61	0.69	0.60	**0.63**
Avg.	**0.37**	**0.61**	**0.71**	
Av UMD				**0.34**
Avg SMB				**-0.14**

5. Chemicals

	Down	Neutral	Up	Avg.
Small	0.50	0.97	0.94	**0.80**
Big	0.56	0.54	0.74	**0.61**
Avg.	**0.53**	**0.75**	**0.84**	
Av UMD				**0.31**
Avg SMB				**0.19**

6. Business Equipment

	Down	Neutral	Up	Avg.
Small	0.31	0.70	1.13	**0.71**
Big	0.25	0.71	1.08	**0.68**
Avg.	**0.28**	**0.70**	**1.10**	
Av UMD				**0.82**
Avg SMB				**0.03**

7. Telecoms

	Down	Neutral	Up	Avg.
Small	0.77	0.89	0.86	**0.84**
Big	0.50	0.42	0.62	**0.51**
Avg.	**0.63**	**0.66**	**0.74**	
Av UMD				**0.10**
Avg SMB				**0.33**

8. Utilities

	Down	Neutral	Up	Avg.
Small	0.64	0.62	0.68	**0.65**
Big	0.23	0.43	0.57	**0.41**
Avg.	**0.44**	**0.52**	**0.63**	
Av UMD				**0.19**
Avg SMB				**0.24**

9. Shops

	Down	Neutral	Up	Avg.
Small	0.18	0.74	1.08	**0.67**
Big	0.31	0.47	0.89	**0.55**
Avg.	**0.25**	**0.60**	**0.99**	
Av UMD				**0.74**
Avg SMB				**0.12**

10. Healthcare

	Down	Neutral	Up	Avg.
Small	0.58	0.94	1.19	**0.90**
Big	0.67	0.62	0.90	**0.73**
Avg.	**0.62**	**0.78**	**1.04**	
Av UMD				**0.42**
Avg SMB				**0.17**

11. Money

	Down	Neutral	Up	Avg.
Small	0.34	0.79	0.93	**0.69**
Big	0.28	0.55	0.71	**0.51**
Avg.	**0.31**	**0.67**	**0.82**	
Av UMD				**0.50**
Avg SMB				**0.17**

12. Other

	Down	Neutral	Up	Avg.
Small	0.07	0.75	1.16	**0.66**
Big	0.13	0.52	0.78	**0.48**
Avg.	**0.10**	**0.63**	**0.97**	
Av UMD				**0.87**
Avg SMB				**0.18**

We first observe the patterns of average monthly returns of 6 value-weighted portfolios formed on *Size* and *Value* in Table 4.1.1. These portfolios are independently sorted from *Small* to *Big* based on their market equity, and from *Low* to *High* based on their book-to-market ratio. The furthest right column represents the average of each of the *Size* halves, whereas the bottom row represents the average of each of the *Value* terciles. The “Avg HML” and “Avg SMB” represent the difference between the average of the *High* portfolio returns and the average of the *Low* portfolio returns, as well as the difference between the average returns of the *Small* portfolio and the average returns of the *Big* portfolio, respectively. These two values give us the supposed monthly premium the SMB and HML trades could generate over the respective time sample.

In the value-weighted Size-Value sort the average returns are increasing as B/M increases (left-to-right) for all of the industries, while holding Size roughly constant. This means that the “value companies” (those companies with high B/M) generate higher excess returns than “growth companies” (with low B/M) across all industries. Thus, the “value” anomaly seems to be an across-industry phenomenon. Furthermore, small companies also generate higher returns than large companies for most of the industries. A notable exception here are Non-Durables, and to some extent Shops, Energy and Business Equipment, where the average size effect is roughly flat, holding B/M constant. This implies that the “size” anomaly varies in effect across industries and leads to less clear-cut patterns even where the size effect is present. In nearly all industries the Small-High intersection portfolio generates the highest returns among the 6 portfolios. Indeed, the highest monthly return of all portfolios is generated by the Small-High intersection portfolio within Business Equipment, yielding a 1.58% average monthly return over the observed time period, when the sub-portfolios are able to be formed. All of these patterns are largely consistent with the Fama-French findings conducted using aggregate market data, implying that the behavior of stocks is to a large extent not conditional on the applied industry disaggregation – as the returns exhibit the same type of general behavior within and across groups.

However, we can also observe that the HML and SMB premiums do differ, sometimes rather substantially, across industries. This is important because it points towards the presence of differing magnitudes of industry effects which can prove useful for the formation of industry-specific anomaly-based trading strategies. Notably, the HML premium is stronger in magnitude than the SMB premium for the majority of industries. The only industry where the SMB premium is stronger than HML are Telecoms (0.09% versus 0.27%), and in the case of Shops it delivers the same premium as HML. Lastly, while the HML premium is positive for all industries, SMB premium enters negative territory for Non-Durables and is rather flat within Business Equipment due to an unexpected pattern within the 'Low B/M' column, whereby small companies provide substantially lower average returns than big companies (0.80% versus 1.15%) . We conclude that in the Size-Value bivariate sort, much of the aggregate data patterns remain the same upon applied industry disaggregation. However, we also observe notable differences in the magnitude of the effects, which imply potential trading opportunities if focus of the anomaly-based trades is put towards specific industries.

Next, we examine the Size-OP value-weighted return patterns. The portfolios are independently sorted from *Small* to *Big* based on their market equity and from *Weak* to *Robust* based on their operating profitability. We observe that the average returns do increase as the operating profitability of the grouped stocks increases, holding Size roughly constant. An exception seem to be big companies within Healthcare and Chemicals, where the trend is somewhat reversed. The implication of this is that large companies, especially within Chemicals, have generated higher average returns if they also exhibited relatively weak profitability – which is a very interesting finding. Small companies in this sort generate higher returns on average than large companies, holding OP roughly constant. The highest average returns (1.58%) appear in the Small-Robust intersection portfolio within Telecoms. Looking at the premiums, the SMB is positive for all portfolio groups, but is nonetheless rather flat within Energy and Non-Durables industry groups. The RMW premium is also positive across industries, but is rather flat within Healthcare and Chemicals. Moreover, the RMW and SMB spreads differ substantially depending on the industry observed. RMW shows a very strong effect within Telecoms and Shops. We conclude that the presence of the OP effect in the average return patterns remains after our industry disaggregation is applied (consistent with Fama-French aggregate data results), as well as substantial differences in the RMW and SMB premiums across industries.

We further move to the analysis of the Size-Investment sort results from Table 4.1.3. The portfolios are again independently sorted from *Small* to *Big* based on their market equity and from *Conservative* to *Aggressive* based on their growth in total assets, a proxy for the size of the companies' investment. We observe that on average the returns increase as the investment variable moves from right to left, holding size variable constant, for most of the industries. The size effect is present with this type of bivariate sort too, with smaller companies showcasing higher returns than larger companies for the majority of the industries. Even though the trend for both the investment and size can be observed, the pattern is much less clear-cut compared to the case of Size-Value sort. Some of the Neutral portfolios generate higher average returns than the average of *Conservative* portfolios. Interestingly, Energy and Telecoms exhibit very flat return patterns, implying that the investment effect is not as strong for these two industries. In fact, within Telecoms, the bottom sub-portfolios containing larger companies exhibit stronger returns with more aggressive investment policies, which is another interesting deviation from the general trend we see in the aggregate market data. It implies that the CMA effect within Telecoms is only present for the small companies. The highest return is observed on the Small-Conservative intersection within the Healthcare industry, yielding 1.67% per month. In terms of premiums, CMA is positive across industries but as noted before largely flat for Telecoms and Energy. SMB is also positive for most industries, but very flat for Non-Durables and Energy. As the premiums do differ substantially between industries (albeit still being positive), we conclude that the pattern indicates a clear presence of industry effects for the investment anomaly as well, and continue to examine the degree of these effects further on in the paper.

Lastly, we observe Table 4.1.4 of 6 portfolios per industry sorted on Size and Momentum variables. The portfolios are again independently sorted from *Small* to *Big* based on their market equity and from *Down* to *Up* based on their cumulative monthly returns in the previous year. Here, we see a very clear pattern for the Momentum variable, holding Size constant. The average returns significantly increase left to right for all industries, and the UMD premiums are positive and of a much greater magnitude compared to previously sorted variables (B/M, OP, INV). Nonetheless, for certain industries such as Business Equipment and Shops the momentum spread is significantly higher than for the rest, demonstrating the potential importance of adopting an industry-specific focus. For others, such as Telecoms and Utilities, the momentum spread is comparatively much lower. We conclude that the momentum anomaly is present in the data after applied industry disaggregation and that the patterns are overall consistent with aggregate data findings, albeit with differing premiums.

Our preliminary analysis of the average monthly return patterns thus clearly demonstrates evidence of anomaly presence within industries, for all of the variables we consider. This is a very important finding in and of itself. If the industry sorted returns were to exhibit very different type of behavior from the aggregate sorts, there would be an evident potential to facilitate more profitable factor trades by adopting an industry-specific focus or, alternatively, by excluding certain industries from a diversified factor trade portfolio. For example, if one of the industries had a very significant negative premium on HML sorts, the implication would be that it is indeed the higher valued stocks (low B/M) that yield higher returns, rather than the lower valued stocks (high B/M) within this industry group. Thus, for a value investor, exclusion of that particular industry would be highly beneficial. Likewise, a hedge fund could collect premiums by pursuing a reverse trade within this industry, effectively an industry-specific LMH strategy. However, the results that we present show us that stocks tend to predominantly exhibit the same return behavior even upon applied industry disaggregation, with very few exceptions. Nonetheless, the pattern analysis also indicates differing magnitudes of anomaly-based industry effects, as in some instances the returns do not strictly increase with the observed variable, as is the case with the aggregate market sampling performed by Fama and French. This implies that the industry focus can be relevant in order to earn relatively higher premiums if factor trading strategies are applied only to certain industry groups. With this insight, we move forward to the construction of industry-specific factor-mimicking portfolios and testing of said portfolios using single-factor market and aggregate risk factor regressions.

4.2 Performance of industry-specific factor portfolios

We first analyze the performance of industry factors compared to the market, by regressing the long-short industry factor portfolios on the excess market returns, in search of a statistically significant alpha. We start with the performance of industry SMB factor, by regressing each industry's SMB portfolio to the excess market return. In the bottom row, we add the performance of the aggregate SMB versus the excess market, for the sake of comparison. Considering that we are observing long-short portfolios, our definition of Sharpe ratio is simply the return of each of the zero-cost portfolio divided by its volatility, without taking out the risk-free rate. In order to avoid misleading inference caused by potential issues of heteroskedasticity and autocorrelation in standard errors, we apply the heteroskedasticity and autocorrelation consistent (HAC) estimators of the variance-covariance matrices as proposed by Newey-West (1987).

Table 4.2.1: Single-factor regressions of industry SMB factor portfolios on excess market return, June 1963 – June 2019; Alphas, Betas and annualized returns are stated in percentage terms.

Industry type:	Alpha (α)	t-stat, t(α)	p-value	Market (β)	t-stat, t(β)	p-value	Ann. Return	Sharpe Ratio
1. NoDur	-0.24	-1.89	0.06	18.27	5.14	0.00	-2.43	-0.21
2. Durbl	0.17	1.00	0.32	9.07	1.67	0.10	1.43	0.10
3. Manuf	0.13	1.01	0.31	4.09	1.14	0.26	1.17	0.11
4. Enrgy	-0.12	-0.80	0.42	30.04	5.97	0.00	-0.50	-0.04
5. Chems	0.12	0.82	0.41	15.10	3.97	0.00	1.54	0.12
6. BusEq	-0.13	-0.85	0.40	26.92	6.28	0.00	-0.82	-0.06
7. Telcm	0.05	0.30	0.76	37.44	6.22	0.00	1.58	0.10
8. Utils	**0.18**	**2.46**	**0.01**	**2.69**	**1.42**	**0.16**	**2.11**	**0.33**
9. Shops	-0.01	-0.09	0.93	18.34	5.43	0.00	0.47	0.04
10. Hlth	-0.01	-0.05	0.96	36.48	8.01	0.00	0.78	0.05
11. Money	0.14	1.16	0.25	-7.73	-1.95	0.05	0.58	0.06
12. Other	0.10	0.79	0.43	7.37	2.94	0.00	1.03	0.09
Agg. SMB	0.09	0.83	0.41	20.4	2.94	0.00	1.88	0.18

As can be seen in Table 4.2.1, the industry SMB returns show very little statistical significance and fail to obtain a significant positive alpha in most cases, regardless if we use the full market sample (aggregate SMB) or industry-disaggregated portfolios. The Sharpe ratios are very low across industry groups. The only industry that exhibits significant alpha are Utilities, which demonstrate an alpha of 0.18% under a 95% confidence interval, and a Sharpe ratio of 0.33 versus the aggregate SMB Sharpe ratio of 0.18. This effect, however, could largely be driven by the very low market beta of the strategy. Additionally, Utilities contain the lowest total number of companies of all industry groups in our data sample, implying that the long-short portfolio strategies might yield a positive premium simply due to these portfolios not being fully diversified. For the rest of the industry and aggregate results, we can confirm the findings of Horowitz (2000) and Van Dijk (2011) who demonstrate that the "size effect" has largely disappeared since the 1980s, following the academic publications highlighting its presence in the previous time period. Another interesting finding is that Non-Durables provide for a negative alpha that is statistically significant under a 90% confidence interval, with a p-value of 0.06. This means that a reverse trade of "BMS" in Non-Durables would have yielded positive risk-adjusted returns, i.e. the big companies within Non-Durables achieved higher returns compared to the small companies over the observed timeframe.

Table 4.2.2: Single-factor regressions of industry HML factor portfolios on excess market return, June 1963 – June 2019; Alphas, Betas and annualized returns are stated in percentage terms.

Industry type:	Alpha (α)	t-stat, t(α)	p-value	Market (β)	t-stat, t(β)	p-value	Ann. Return	Sharpe Ratio
1. NoDur	**0.31**	**2.37**	**0.02**	**8.88**	**1.78**	**0.08**	**3.81**	**0.37**
2. Durbl	**0.42**	**2.38**	**0.02**	**-10.52**	**-1.74**	**0.08**	**3.28**	**0.22**
3. Manuf	**0.33**	**2.30**	**0.02**	**0.10**	**0.02**	**0.99**	**3.44**	**0.32**
4. Enrgy	**0.58**	**3.33**	**0.00**	**0.32**	**0.06**	**0.96**	**6.22**	**0.45**
5. Chems	**0.35**	**2.13**	**0.03**	**11.35**	**1.94**	**0.05**	**4.03**	**0.28**
6. BusEq	**0.54**	**2.91**	**0.00**	**-12.82**	**-2.14**	**0.03**	**4.83**	**0.35**
7. Telcm	0.20	1.06	0.29	-19.07	-2.66	0.01	0.08	0.01
8. Utils	**0.36**	**3.38**	**0.00**	**-12.32**	**-3.95**	**0.00**	**3.24**	**0.38**
9. Shops	0.09	0.57	0.57	-0.74	-0.12	0.91	0.41	0.04
10. Hlth	**0.39**	**2.25**	**0.02**	**-0.85**	**-0.17**	**0.87**	**3.69**	**0.27**
11. Money	0.25	1.90	0.06	-2.03	-0.53	0.60	2.39	0.24
12. Other	**0.32**	**2.02**	**0.04**	**-12.91**	**-2.64**	**0.01**	**2.34**	**0.20**
Agg. HML	**0.39**	**2.82**	**0.00**	**-16.2**	**-3.10**	**0.00**	**3.27**	**0.34**

Proceeding with the analysis of industry HML portfolios, a much higher presence of the value anomaly is clearly demonstrated. Most of the industries generate a monthly risk-adjusted return not captured by the historical market premium, with Energy showing the highest alpha of 0.58% and a return of 6.22% annualized. The aggregate HML portfolio displays high statistical significance when regressed on the excess market return, mostly driven by the pre-1991 period before the wide popularization of the value anomaly in the academic literature (see Section 4.4). In volatility-adjusted terms observed through the Sharpe ratio of constructed portfolios, three industries deliver results exceeding the aggregate HML strategy, namely: Energy, Utilities and Non-Durables. The conclusion here is that for the value effect, applied industry disaggregation clearly matters. Focusing one's strategy on the aforementioned three industries would have delivered better volatility-adjusted performance than the aggregate factor strategy. This is not surprising, as it is exactly these industries that exhibited large HML premiums in Table 4.1.1. Moreover, most industries deliver statistically significant alpha that is higher or very close to that of the aggregate HML portfolio. The high statistical presence of the value anomaly across industries, might also pinpoint to the overall value effect being driven by the industry value effect. However, Telecoms and Shops are clear exceptions over the observed time horizon.

Table 4.2.3: Single-factor regressions of industry RMW factor portfolios on excess market return, June 1963 – June 2019; Alphas, Betas and annualized returns are stated in percentage terms.

Industry type:	Alpha (α)	t-stat, t(α)	p-value	Market (β)	t-stat, t(β)	p-value	Ann. Return	Sharpe Ratio
1. NoDur	**0.33**	**3.22**	**0.00**	**-13.48**	**-4.16**	**0.00**	**2.75**	**0.31**
2. Durbl	0.19	0.84	0.40	1.19	0.24	0.81	0.96	0.06
3. Manuf	**0.27**	**2.42**	**0.02**	**-11.08**	**-3.29**	**0.00**	**2.17**	**0.23**
4. Enrgy	**0.29**	**2.29**	**0.02**	**-13.73**	**-3.96**	**0.00**	**2.02**	**0.19**
5. Chems	0.05	0.32	0.75	-9.42	-2.31	0.02	-0.95	-0.07
6. BusEq	**0.36**	**1.93**	**0.05**	**-32.82**	**-5.52**	**0.00**	**1.22**	**0.08**
7. Telcm	**0.42**	**1.96**	**0.05**	**-17.86**	**-2.64**	**0.01**	**2.32**	**0.13**
8. Utils	0.16	1.66	0.10	0.43	0.14	0.89	1.71	0.22
9. Shops	**0.35**	**2.98**	**0.00**	**-7.06**	**-1.83**	**0.07**	**3.34**	**0.35**
10. Hlth	0.20	1.18	0.24	-28.98	-5.13	0.00	-0.74	-0.05
11. Money	-	-	-	-	-	-	-	-
12. Other	0.20	1.26	0.21	-6.09	-1.11	0.27	1.30	0.11
Agg. RMW	**0.32**	**2.87**	**0.00**	**-11.20**	**-2.55**	**0.01**	**2.86**	**0.38**

Turning our focus to the operating profitability anomaly, we see somewhat mixed results. While there are several industries delivering positive alphas with high statistical significance, most notably Non-Durables and Shops, we also observe that none of the strategies performed better in volatility-adjusted terms than the aggregate RMW factor. Business Equipment and Telecoms yield positive results, but after applying Newey-West robust standard errors the alpha t-statistics fall below 2. Overall, the RMW trades in six of the industry groups deliver risk-adjusted positive performance. However, compared to the aggregate portfolio, applied industry disaggregation is not very effective for pursuing RMW-based trading strategies, as much of the anomaly effects are lost in the subsets of aggregate data, showcased by comparatively lower industry-specific alphas and Sharpe ratios. Only Shops provide higher annualized returns than the aggregate RMW, but even this industry group demonstrates higher volatility of returns, leading to a weaker performance in volatility-adjusted terms.

Table 4.2.4: Single-factor regressions of industry CMA factor portfolios on excess market return, June 1963 – June 2019; Alphas, Betas and annualized returns are stated in percentage terms.

Industry type:	Alpha (α)	t-stat, t(α)	p-value	Market (β)	t-stat, t(β)	p-value	Ann. Return	Sharpe Ratio
1. NoDur	0.19	1.84	0.07	-1.90	-0.57	0.57	1.81	0.21
2. Durbl	**0.42**	**2.59**	**0.01**	**-11.99**	**-2.54**	**0.01**	**3.33**	**0.24**
3. Manuf	**0.31**	**3.10**	**0.00**	**-7.54**	**-2.27**	**0.02**	**2.94**	**0.34**
4. Enrgy	0.06	0.41	0.68	-8.50	-1.88	0.06	-0.59	-0.05
5. Chems	**0.27**	**2.35**	**0.02**	**1.73**	**0.42**	**0.67**	**2.72**	**0.23**
6. BusEq	**0.38**	**3.09**	**0.00**	**-10.51**	**-2.69**	**0.01**	**3.37**	**0.30**
7. Telcm	0.10	0.55	0.58	-5.35	-1.06	0.29	-0.31	-0.02
8. Utils	**0.23**	**3.06**	**0.00**	**-7.16**	**-3.32**	**0.00**	**2.18**	**0.35**
9. Shops	**0.24**	**2.37**	**0.02**	**-13.20**	**-3.50**	**0.00**	**1.60**	**0.18**
10. Hlth	**0.46**	**3.70**	**0.00**	**-5.80**	**-1.92**	**0.06**	**4.76**	**0.46**
11. Money	-	-	-	-	-	-	-	-
12. Other	**0.51**	**4.49**	**0.00**	**-14.71**	**-4.82**	**0.00**	**4.78**	**0.49**
Agg. CMA	**0.37**	**4.10**	**0.00**	**-17.60**	**-5.24**	**0.00**	**3.09**	**0.45**

Looking at the industry CMA factor strategies, we again notice strong effects for several industries. Healthcare-focused strategy yields the highest annualized return of the single-industry groups and one of the highest alphas, with very strong statistical significance. It also results in a Sharpe ratio that beats that of the aggregate CMA strategy. This implies that Healthcare companies that tended to increase their assets delivered returns significantly worse than their counterparts with more conservative investment policies. Interestingly, the industry group “Other” provides for the highest alpha and annualized return overall, as well as the highest Sharpe ratio which is slightly better than that of aggregate CMA strategy. This tells us that the drivers of CMA anomalous returns are most likely not the industry-specific fundamentals, as “Other” group within itself contains a set of widely differing companies in terms of pursued economic activities, products and macroeconomic exposures. We thus hypothesize that the drivers of CMA premiums could instead be the general misallocation of capital investments across industries, punishing companies which invest heavily in potentially unprofitable projects, and rewarding companies with more conservative investments in general. Nonetheless, we can also clearly see that two of the industries, Energy and Telecoms, perform very poorly in their respective CMA-sorted portfolios, with very low statistical significance and negative annualized returns, which was also observed in Section 4.1. The optimal CMA-based strategy could thus be one of exclusion of certain industries, rather than one of focus on a single best-performing industry. In the observed timeframe, the optimal risk-reward choice of CMA premium pursuit would have been the exclusion of Energy and Telecom companies from the aggregate CMA portfolio.

Table 4.2.5: Single-factor regressions of industry UMD factor portfolios on excess market return, June 1963 – June 2019; Alphas, Betas and annualized returns are stated in percentage terms.

Industry type:	Alpha (α)	t-stat, t(α)	p-value	Market (β)	t-stat, t(β)	p-value	Ann. Return	Sharpe Ratio
1. NoDur	**0.65**	**4.64**	**0.00**	**-16.61**	**-2.14**	**0.03**	**5.99**	**0.45**
2. Durbl	**0.67**	**4.02**	**0.00**	**-16.13**	**-1.82**	**0.07**	**5.44**	**0.30**
3. Manuf	**0.66**	**4.12**	**0.00**	**-9.51**	**-1.63**	**0.10**	**6.64**	**0.50**
4. Enrgy	**0.44**	**2.07**	**0.04**	**-14.21**	**-1.97**	**0.05**	**2.15**	**0.11**
5. Chems	**0.39**	**2.13**	**0.03**	**-9.99**	**-1.30**	**0.19**	**2.47**	**0.15**
6. BusEq	**0.91**	**5.19**	**0.00**	**-8.54**	**-1.25**	**0.21**	**9.24**	**0.52**
7. Telcm	0.31	1.15	0.25	-17.35	-1.95	0.05	0.52	0.03
8. Utils	0.18	1.26	0.21	-9.89	-1.48	0.14	0.79	0.07
9. Shops	**0.78**	**4.84**	**0.00**	**-10.91**	**-1.67**	**0.10**	**7.77**	**0.54**
10. Hlth	**0.48**	**3.07**	**0.00**	**-9.21**	**-1.53**	**0.13**	**4.02**	**0.27**
11. Money	**0.62**	**3.62**	**0.00**	**-23.35**	**-2.32**	**0.02**	**4.8**	**0.31**
12. Other	**0.96**	**5.26**	**0.00**	**-14.52**	**-1.87**	**0.06**	**9.63**	**0.59**
Agg. UMD	**0.72**	**4.79**	**0.00**	**-13.20**	**-1.58**	**0.12**	**6.97**	**0.48**

The within-industry momentum strategies show high levels of statistical significance with only two industries, Telecoms and Utilities, exhibiting a p-value greater than 0.05. Moreover, the alphas and annualized returns generated by the industry momentum strategies are the highest in absolute terms for most industries compared to other industry-specific portfolios. This confirms the widespread presence of momentum effect within industries, which is largely consistent with the findings of Moskowitz and Grinblatt (1999). Even though Telecoms and Utilities long-short portfolios also generate positive premiums, their rather small annualized returns do present an interesting finding.

We next move towards conducting the analysis of how well the industry-specific strategies perform when tested directly against their respective aggregate factors. We do this by regressing each of the industry-specific factors on the established aggregate factor, for each of the five anomalies and twelve industries. We present the results below, with the aggregate factor returns included at the bottom row for the ease of comparison.

Table 4.2.6: Factor regressions of industry SMB portfolios on aggregate SMB factor; June 1963 – June 2019; Alphas, Betas, annualized returns and mean monthly returns are stated in percentage terms.

Industry type:	Alpha (α)	t-stat, t(α)	p-value	Agg. SMB (β)	t-stat, t(β)	Ann.Ret.	Sharpe Ratio	Mean
1. NoDur	**-0.31**	**-3.53**	**0.00**	**82.00**	**11.79**	**-2.43**	**-0.21**	**-0.15**
2. Durbl	0.06	0.51	0.61	75.74	12.79	1.43	0.10	0.22
3. Manuf	-0.01	-0.21	0.83	80.30	26.11	1.17	0.11	0.15
4. Enrgy	-0.10	-0.66	0.51	72.01	7.28	-0.50	-0.04	0.04
5. Chems	0.05	0.44	0.66	74.92	19.85	1.54	0.12	0.20
6. BusEq	-0.19	-1.83	0.07	100.86	16.07	-0.82	-0.06	0.01
7. Telcm	0.08	0.47	0.64	86.46	10.78	1.58	0.10	0.24
8. Utils	**0.15**	**2.54**	**0.01**	**21.29**	**8.65**	**2.11**	**0.33**	**0.19**
9. Shops	-0.07	-1.22	0.22	80.23	15.36	0.47	0.04	0.09
10. Hlth	-0.07	-0.61	0.54	127.55	7.19	0.78	0.05	0.18
11. Money	-0.03	-0.26	0.80	59.72	16.34	0.58	0.06	0.09
12. Other	-0.02	-0.29	0.77	80.00	19.83	1.03	0.09	0.14
Aggregate SMB						1.88	0.18	0.20

As can be seen in the Table 4.2.6, the industry-specific SMB factors perform rather poorly when regressed on the aggregate SMB factor. Almost all the alphas are negative or very close to zero, with very little statistical significance shown in the regressions. The aggregate factor explains the returns of the industry-specific portfolios with very high significance, as the industry portfolios load heavily onto the aggregate SMB with a positive slope. The beta t-stats are very high across industries and the coefficients are rather high as well, with Business Equipment having a beta coefficient of 1.01 - implying very similar covariation with the aggregate factor returns. We also notice that industry groups that contain the highest number of stocks overall (e.g. Manufacturing, Business Equipment, Other), tend to provide for higher t-stats as well. The explanation for such high explanatory power of the aggregate factor is simple. Using the median NYSE Size breakpoints leads to many of the truly big companies in the market also being above-industry-median when sorted in their respective industry groups. Considering the sub-portfolios are value-weighted, these types of companies dominate the return behavior of the overall Big portfolio throughout the sorting process, whereas the Small portfolios are more diversified across industries. Indeed, the only industry that remains unexplained by the aggregate SMB factor are the Utilities, despite having the same type of sorting procedure applied. Most of its alpha is driven by the low SMB beta coefficient and less volatile return behavior across the time sample (see Section 4.4). As pointed out before, Non-Durables result in a statistically significant negative alpha. Nonetheless, the beta slope is positive with respect to the aggregate factor at 0.82, meaning that Non-Durables SMB also comoves in the same direction as the aggregate SMB.

Table 4.2.7: Factor regressions of industry HML portfolios on aggregate HML factor; June 1963 – June 2019; Alphas, Betas, annualized returns and mean monthly returns are stated in percentage terms.

Industry type:	Alpha (α)	t-stat, t(α)	p-value	Agg. HML(β)	t-stat, t(β)	Ann.Ret.	Sharpe Ratio	Mean
1. NoDur	**0.22**	**2.03**	**0.04**	**44.05**	**9.02**	**3.81**	**0.37**	**0.36**
2. Durbl	0.17	1.01	0.31	61.74	7.52	3.28	0.22	0.36
3. Manuf	0.14	1.40	0.16	62.60	11.17	3.44	0.32	0.33
4. Enrgy	**0.45**	**2.83**	**0.00**	**42.47**	**4.27**	**6.22**	**0.45**	**0.58**
5. Chems	0.25	1.67	0.09	52.56	5.58	4.03	0.28	0.41
6. BusEq	0.23	1.52	0.13	78.32	8.14	4.83	0.35	0.47
7. Telcm	-0.09	-0.54	0.59	63.57	6.84	0.08	0.01	0.10
8. Utils	**0.22**	**2.15**	**0.03**	**24.24**	**3.83**	**3.24**	**0.38**	**0.30**
9. Shops	-0.11	-0.92	0.36	62.27	9.73	0.41	0.04	0.09
10. Hlth	0.18	1.39	0.17	65.47	8.54	3.69	0.27	0.38
11. Money	0.08	0.91	0.37	50.08	8.06	2.39	0.24	0.24
12. Other	0.01	0.12	0.91	77.97	12.48	2.34	0.20	0.25
Agg. HML						3.27	0.34	0.31

Looking at the HML factor regressions, we notice several industries that provide statistically significant alphas: Non-Durables, Energy and Utilities. Compared to the industry HML regressions in the single-factor market regression framework above, fewer industries seem to beat the aggregate HML portfolio. Indeed, Durables, Manufacturing, Chemicals, Business Equipment, Healthcare and Other industry groups highly load onto the aggregate HML factor, losing much of their previously reported outperformance. Nonetheless, the three industry groups that show both outperformance in the single-factor market regression and respective factor framework deliver clear evidence of the importance of industry focus when pursuing factor investing strategies. Industry-based anomaly strategy comprising of stocks only within these three industries would have yielded significant premiums compared to the fully-diversified aggregate factor strategy. The reasoning for this lies in the overall industry size and value characteristics. Due to differing Size medians and B/M percentile dispersions within these industry groups, the size and value effects are more pronounced. Of the four industries, Energy companies exhibit the strongest presence of the value effect over the observed time period, with an annualized return of 6.22% and a Sharpe ratio of 0.45. Considering these are self-financing portfolios, such trade premiums are significant. Indeed, when we test the excess market return through our volatility-adjusted performance framework, it yields a Sharpe ratio of 0.35 and an annualized return of 5.30% over the same timeframe. Energy HML thus clearly outperforms the market on both metrics. Lastly, while all the betas are still highly significant across industries, they do provide for a lesser explanatory power than the case of SMB portfolios presented above. This is driven by the fact that within-industry B/M distribution, as opposed to Size distribution, provides for a much greater movement of companies across sub-portfolios each year when they are sorted with respect to industry breakpoints. We further test the strategies with respect to full FF5 & Momentum regressions, and for some of them the alpha persists (Appendix D), confirming risk-adjusted outperformance across the observed time sample.

Table 4.2.8: Factor regressions of industry RMW portfolios on aggregate RMW factor; June 1963 – June 2019; Alphas, Betas, annualized returns and mean monthly returns are stated in percentage terms.

Industry type:	Alpha (α)	t-stat, t(α)	p-value	Agg. RMW(β)	t-stat, t(β)	Ann.Ret.	Sharpe Ratio	Mean
1. NoDur	0.16	1.64	0.10	37.29	4.26	2.75	0.31	0.26
2. Durbl	0.13	0.61	0.54	25.34	2.30	0.96	0.06	0.19
3. Manuf	0.07	0.65	0.52	57.56	4.20	2.17	0.23	0.22
4. Enrgy	0.16	1.30	0.19	22.76	1.75	2.02	0.19	0.21
5. Chems	-0.09	-0.63	0.53	34.89	2.53	-0.95	-0.07	0.00
6. BusEq	-0.10	-0.72	0.47	113.78	12.28	1.22	0.08	0.19
7. Telcm	0.09	0.50	0.62	91.88	8.47	2.32	0.13	0.32
8. Utils	0.11	1.06	0.29	22.72	2.93	1.71	0.22	0.17
9. Shops	0.16	1.40	0.16	57.11	6.78	3.34	0.35	0.31
10. Hlth	-0.24	-1.42	0.15	111.50	4.50	-0.74	-0.05	0.04
11. Money	-	-	-	-	-	-	-	-
12. Other	-0.11	-0.98	0.33	106.16	13.63	1.30	0.11	0.17
Agg. RMW						2.86	0.38	0.26

The results of the industry-specific operating profitability regressions provide for interesting insights. While six of the industry portfolios exhibit positive monthly alphas in the single-factor market regressions, none of these portfolios perform sufficiently well when tested against the aggregate RMW factor over the observed timeframe. Such results could have been expected, considering that the six aforementioned portfolios do yield lower levels of volatility-adjusted returns compared to the aggregate factor strategy, as well as lower levels of annualized returns in general. An interesting observation is also that Energy RMW does not have a statistically significant beta coefficient, meaning that the Size-OP sort within this industry does result in companies being sorted differently compared to the way they would be in the aggregate portfolio sorts. However, such sort also results in a relatively low return premium (AR of 2.02%), which also adds to a statistically insignificant alpha intercept. Certain industries, such as Shops, do however provide for higher annualized returns, and only a slightly lower Sharpe ratio compared to the aggregate RMW strategy, which could have been of interest to investors seeking to limit their trading costs by investing in a smaller subset of companies than the aggregate market, thereby reducing their rebalancing turnover over the studied time sample. Nonetheless, such strategies are ultimately inferior to the aggregate factor strategy in the case of RMW and could lead to an overexposure to Shops stocks only. We thus provide evidence that the operating profitability anomaly is indeed an aggregate market asset pricing phenomenon, but one that has less pronounced "industry effects" in the applied industry disaggregation, thereby having limited benefits for industry-focused investors.

Table 4.2.9: Factor regressions of industry CMA portfolios on aggregate CMA factor; June 1963 – June 2019; Alphas, Betas, annualized returns and mean monthly returns are stated in percentage terms.

Industry type:	Alpha (α)	t-stat, t(α)	p-value	Agg. CMA(β)	t-stat, t(β)	Ann.Ret.	Sharpe Ratio	Mean
1. NoDur	0.08	0.94	0.35	38.06	6.22	1.81	0.21	0.18
2. Durbl	0.15	1.09	0.27	76.38	9.91	3.33	0.24	0.36
3. Manuf	0.08	1.02	0.31	70.81	15.03	2.94	0.34	0.27
4. Enrgy	-0.12	-0.85	0.40	47.32	5.26	-0.59	-0.05	0.02
5. Chems	0.19	1.63	0.10	34.44	3.36	2.72	0.23	0.28
6. BusEq	0.12	1.01	0.31	77.24	8.47	3.37	0.30	0.33
7. Telcm	-0.04	-0.24	0.81	37.86	3.39	-0.31	-0.02	0.07
8. Utils	**0.15**	**2.00**	**0.05**	**15.21**	**3.71**	**2.18**	**0.35**	**0.20**
9. Shops	-0.01	-0.15	0.88	64.64	8.02	1.60	0.18	0.17
10. Hlth	**0.31**	**2.74**	**0.01**	**46.18**	**7.59**	**4.76**	**0.46**	**0.43**
11. Money	-	-	-	-	-	-	-	-
12. Other	**0.23**	**2.26**	**0.02**	**71.91**	**11.08**	**4.78**	**0.49**	**0.43**
Agg. CMA						3.09	0.45	0.27

Observing the investment anomaly, we see that three industry groups retain positive statistically significant alphas when regressed on the aggregate CMA factor: Utilities, Healthcare and Other. These three industry groups exhibited the highest t-stats in the single-factor market regressions in Table 4.2.4, and their within-industry CMA effects remain unexplained by the aggregate CMA factor over the observed time period. More interestingly, a total of 6 other industries which show positive results in the single-factor market regressions lose their statistical significance in the aggregate factor regressions, with some resulting in negative alphas, albeit statistically insignificant. This implies that pursuing industry-specific CMA factor strategies yields mixed results. Only Healthcare as a separate industry group delivers higher returns and a higher Sharpe ratio than the aggregate CMA strategy, whereas the outperformance of the Other industry group can most likely be attributed to the exclusion of certain industry types from the portfolios, such as Telecoms and Energy. Indeed, it seems that the relatively more aggressive investment policies have yielded higher returns for companies in these industries, which is a clear deviation from the pattern that we observe with the aggregate data. This remains the case even when we study the two industries' CMA premiums across different time samples (Section 4.4 of the thesis). We conclude that some industry-focused CMA strategies have delivered outperformance over the studied period, but the optimal strategy could indeed have been one of exclusion of Telecoms and Energy from the aggregate portfolio, rather than adopting an industry-specific focus.

Table 4.2.10: Factor regressions of industry UMD portfolios on aggregate UMD factor; June 1963 – June 2019; Alphas, Betas, annualized returns and mean monthly returns are stated in percentage terms.

Industry type:	Alpha (α)	t-stat, t(α)	p-value	Agg. UMD(β)	t-stat, t(β)	Ann.Ret.	Sharpe Ratio	Mean
1. NoDur	**0.19**	**1.85**	**0.06**	**56.88**	**8.57**	**5.99**	**0.45**	**0.56**
2. Durbl	0.10	0.63	0.53	73.56	8.50	5.44	0.30	0.58
3. Manuf	0.13	1.41	0.16	73.02	22.51	6.64	0.50	0.61
4. Enrgy	-0.09	-0.46	0.65	70.61	8.58	2.15	0.11	0.36
5. Chems	-0.13	-0.70	0.49	72.17	6.21	2.47	0.15	0.34
6. BusEq	**0.30**	**2.06**	**0.04**	**87.54**	**11.44**	**9.24**	**0.52**	**0.87**
7. Telcm	-0.26	-1.17	0.24	74.04	12.26	0.52	0.03	0.21
8. Utils	-0.17	-1.49	0.14	45.42	8.64	0.79	0.07	0.13
9. Shops	**0.23**	**1.77**	**0.08**	**74.94**	**10.48**	**7.77**	**0.54**	**0.72**
10. Hlth	0.04	0.34	0.73	61.19	11.56	4.02	0.27	0.42
11. Money	-0.03	-0.23	0.82	80.28	10.26	4.80	0.31	0.50
12. Other	**0.29**	**2.46**	**0.01**	**91.37**	**19.96**	**9.63**	**0.59**	**0.89**
Agg. UMD						6.97	0.48	0.65

Lastly, we examine the industry-specific UMD regressions presented in the table above. Perhaps surprisingly, we notice that much of the explanatory power of the industry focused strategies can be attributed to the aggregate UMD factor. The beta coefficients are strongly positive, with very high t-stats. Only Business Equipment and Other industry group exhibit positive statistically significant alphas with a p-value of less than 0.05. Non-Durables and Shops follow, but with alpha significance only under a p-value of 10%. These findings are somewhat contrary to the findings of Moskowitz and Grinblatt (1999), who show that industry momentum strategies appear highly profitable even after controlling for individual stock momentum. The reason for this is twofold. Firstly, we adopt a different methodology to said authors both in terms of industry groupings and factor construction. We opt for four digit SIC classifications of 12 industries using bivariate, value-weighted 2x3 sorts on size and momentum in order to remain consistent with Fama-French methodology; whereas their research focuses on two-digit SIC code groups of 20 industries, similar to that employed by Boudoukh, Richardson and Whitelaw (1994). The result of this is that our industry groups contain larger sets of companies with wider attributes and are much more dependent on the Size sort. Secondly, Moskowitz-Grinblatt focus their portfolio construction on industry groups as a whole, rather than within-industry best performing stocks, ultimately building equal-weighted momentum strategies of entire industries – a significantly different methodology to ours, which is aimed at isolating “industry effects” of individual stocks within each industry and comparing it to the aggregate UMD portfolio.

4.3 Combined Industry Strategies

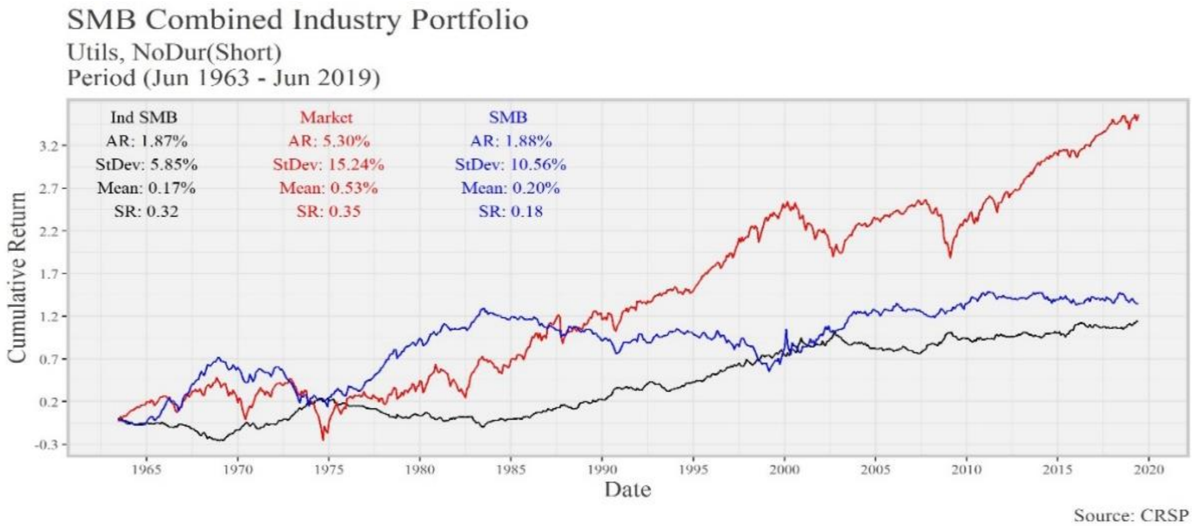
Having closely examined the performance of industry-specific zero-cost portfolios through market and factor regressions, we turn to the performance evaluation of combined industry strategies. As noted before, while some of the industries do report highly statistically significant alphas both with respect to excess market returns and the aggregate factor returns, cautious investors might not want to be exposed to a single industry in their pursuit of ‘alpha’ returns. We also note that for some of the analyzed factors (notably CMA), exclusion of poor-performing industries rather than a single-industry focus might be a more optimal strategy. We thus form *combined industry strategies* for three of the factors, consisting of portfolios of stocks that are assigned only to industries which yielded positive results in the prior analysis. We exclude only the RMW factor from this analysis, as we have previously demonstrated that applied industry-disaggregation posts weak results compared to the aggregate RMW strategy, as none of the industry groups perform well in the factor regressions. The HML combined industry strategy is built as an equal-weighted portfolio of Non-Durables HML, Energy HML, and Utilities HML industry-specific trades, effectively by taking the average of the three single-industry portfolios. The CMA strategy is constructed as an equal-weighted portfolio of Healthcare CMA, Utilities CMA and Other CMA groups, and lastly the UMD combined industry strategy is formed as an equal-weighted portfolio of Business Equipment UMD and Other UMD factors. We also showcase the SMB Industry Effects trade, which is constructed by taking a long position in the Utilities SMB and taking a short position in Non-Durables SMB, due to its strongly negative alpha exhibited before. We present the risk-adjusted performance with respect to all five aggregate factors and the market premium (FF5 + MOM regressions) below.

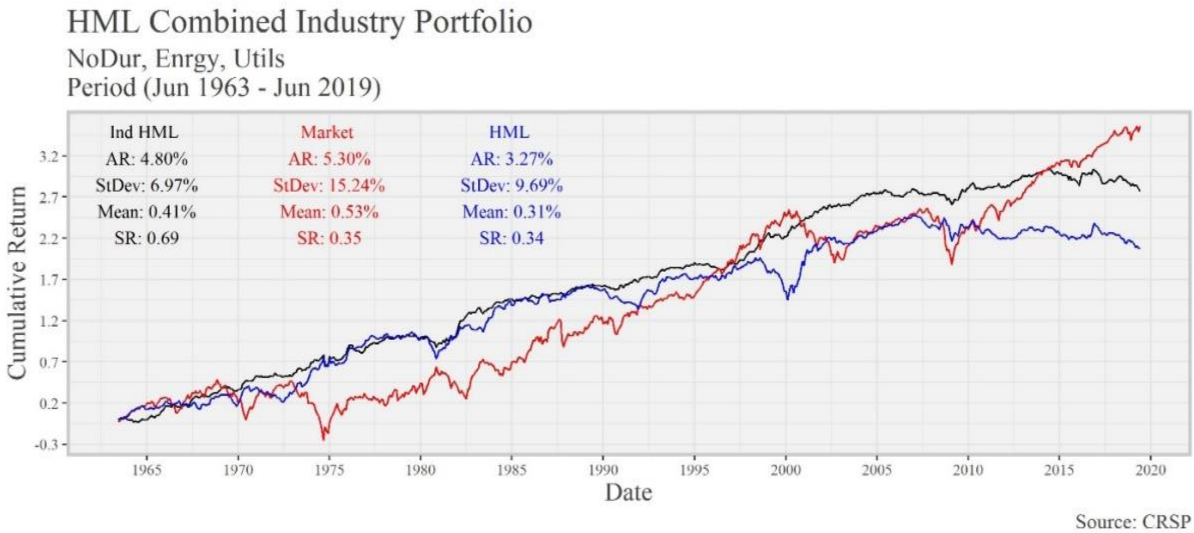
Table 4.3: Combined Industry Strategies Diagnostics. The Table presents the regression results of anomaly-based industry strategies using several combined high-performing industries per each factor. The strategies are then regressed on the five aggregate factors (SMB, HML, RMW, CMA, UMD) and the historical excess market returns ($R_m - R_f$). The time period is June 1963 – June 2019, and the data includes monthly returns. The coefficients are expressed as percentages.

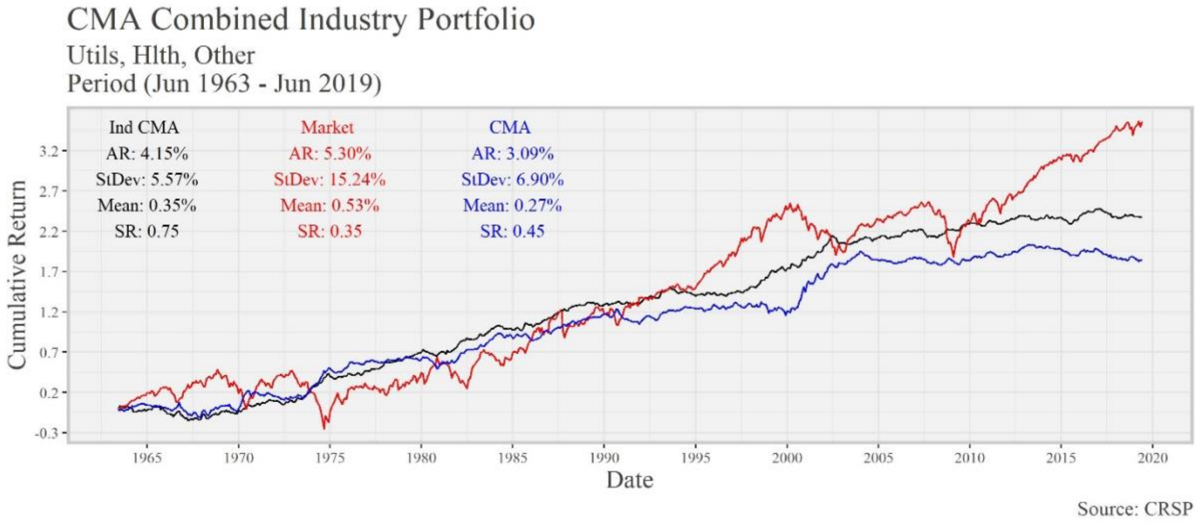
	Alpha (α)	$R_m - R_f$	SMB	HML	RMW	CMA	UMD	R^2
SMB Industry Effects Strategy								
Coef.	**0.18**	-0.04	**-28.62**	-8.04	6.39	11.65	3.45	
t-Statistic	**3.36**	-0.03	**-11.31**	-2.30	1.27	2.34	2.09	0.33
p-Value	**0.00**	0.98	**0.00**	0.02	0.20	0.02	0.04	
HML Combined Industry Strategy								
Coef.	**0.28**	2.23	9.43	**43.16**	-6.88	-6.05	0.26	
t-Statistic	**3.60**	1.00	2.86	**8.74**	-1.97	-1.04	0.13	0.31
p-Value	**0.00**	0.32	0.00	**0.00**	0.05	0.30	0.90	
CMA Combined Industry Strategy								
Coef.	**0.24**	-1.17	-1.85	1.34	0.20	**41.68**	0.85	
t-Statistic	**3.82**	-0.74	-0.81	0.35	0.06	**7.04**	0.50	0.31
p-Value	**0.00**	0.46	0.42	0.73	0.95	**0.00**	0.62	
UMD Combined Industry Strategy								
Coef.	**0.33**	0.72	-8.08	-0.59	1.38	-6.58	**89.33**	
t-Statistic	**3.55**	0.21	-1.50	-0.09	0.20	-0.73	**24.35**	0.75
p-Value	**0.00**	0.83	0.14	0.93	0.84	0.47	**0.00**	

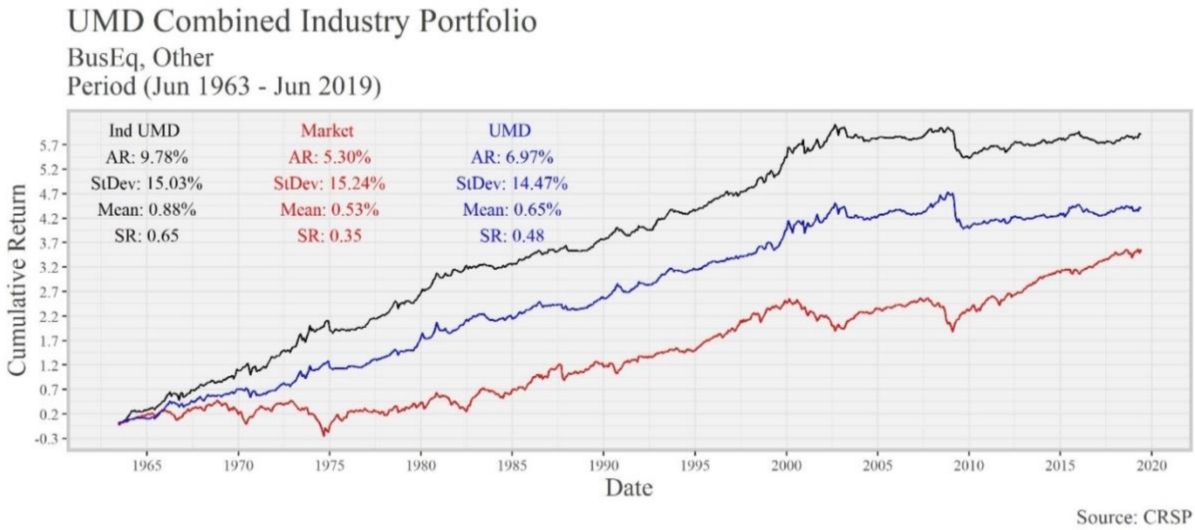
As expected, each of the combined industry portfolios (HML, CMA, UMD) loads strongly onto their respective aggregate factors, with positive slopes and very high statistical significance. This is particularly true for the UMD combined industry strategy, where many of the companies sorted into *Up* and *Down* sub-portfolios across industries follow the same return behavior in the aggregate dataset and in the within-industry dataset, leading to a very high R-squared of 75%. However, all four of the combined industry factor strategies do deliver statistically significant alpha returns during the observed timeframe even when adjusted for all of the established risk factors. The highest alpha is generated by the UMD strategy, whereas the highest statistical significance of the positive intercept is demonstrated by the CMA strategy. The results show that for investors seeking not to be exposed to a single industry, a well-diversified portfolio can still be constructed by using a subset of several high performing industries with respect to the market and the aggregate factor strategy. While pursuing a combined industry strategy lowers the annualized returns achieved from the top-performing single industry factor strategies; it also delivers a substantially higher Sharpe Ratio, as a result of further diversification. We present the cumulative return graphs below.

Graphs 4.3.1: Cumulative returns of the combined industry strategies, compared to excess market returns and aggregate factor returns. "Market" refers to excess market return, "Ind" represents the combined industry strategy, whereas the factors are downloaded from Kenneth French's website. Sharpe Ratio is the return of the long-short strategy, divided by its volatility









As can be seen from the charts above, while all of the combined industry strategies deliver alphas over the observed time period, three of them do not generate cumulative returns higher than the excess market portfolio. However, the selected industry UMD strategy significantly outperforms the market in cumulative returns, as well as in volatility-adjusted terms. HML and CMA combined industry trades also deliver significantly higher Sharpe Ratios compared to the market and to their respective factors, in the range of 0.65 to 0.75. SMB Industry trade performs rather poorly in cumulative returns, as one might expect, but due to its low volatility it yields a Sharpe Ratio similar to that of the market. The correlations of cumulative returns between the combined industry strategy and the aggregate factor strategies are also notably high, as expected with the strong factor loadings described before, a result of the sorting procedure that we apply. However, a portion of the premiums remains unexplained over the observed timeframe, implying that combined industry strategies would have allowed for significant risk-adjusted alphas.

4.4 Performance of industry portfolios over different time samples

Having established that anomalous above-average returns are present in the within-industry formed long-short portfolios, and that their differing premiums would have allowed for profitable single-industry and combined-industry trades (albeit ignoring trading costs, taxations, and similar frictions), we turn to the examination of the performance of industry portfolios over different time horizons. If the positive risk-adjusted returns of high-performing industries are persistent, the interpretation is clear – some industries allow for greater premiums to be "arbitraged" by factor investors. If, on the other hand, the 'alphas' are not persistent, the application of industry-specific strategies is time sensitive and therefore significantly less robust. We split the dataset into two equal timeframes: 1963-1991 and 1991-2019. We present the findings below.

Table 4.4.1:

Industry-specific diagnostics **(1963-1991)**, all the results reported are in percentage terms except for t-statistics. Alpha refers to single-factor market regression (CAPM framework). Columns show respective industry groups.

	NoDur	Durbl	Manu	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money	Other
SMB (alpha)	-0.11	0.37	0.13	0.00	0.27	-0.06	**0.47**	**0.16**	0.07	0.00	0.05	0.23
SMB (t-stat)	-0.56	1.78	0.81	-0.01	1.69	-0.30	**1.99**	**2.99**	0.39	0.02	0.30	1.01
SMB (AR)	-1.16	4.58	1.48	0.44	3.20	-0.41	**6.11**	**1.83**	1.04	0.54	0.14	2.63
SMB (SR)	-0.11	0.33	0.14	0.04	0.29	-0.03	**0.43**	**0.35**	0.09	0.04	0.01	0.25
HML (alpha)	**0.44**	**0.50**	**0.54**	**0.78**	**0.68**	**0.67**	0.28	**0.33**	0.20	**0.45**	**0.39**	**0.49**
HML (t-stat)	**2.68**	**2.61**	**3.25**	**4.39**	**3.40**	**3.03**	1.20	**2.21**	1.11	**2.00**	**1.99**	**2.50**
HML (AR)	**5.12**	**4.42**	**5.71**	**8.37**	**7.89**	**7.21**	0.65	**3.11**	1.28	**4.83**	**4.24**	**4.92**
HML (SR)	**0.55**	**0.35**	**0.61**	**0.70**	**0.70**	**0.53**	0.04	**0.37**	0.13	**0.34**	**0.41**	**0.43**
RMW (alpha)	0.18	-0.08	0.06	**0.27**	-0.19	0.11	0.09	0.11	**0.53**	-0.05	0.03	0.06
RMW (t-stat)	1.22	-0.41	0.41	**1.96**	-1.18	0.50	0.36	0.65	**3.13**	-0.32	0.14	0.30
RMW (AR)	1.49	-1.73	0.30	**2.53**	-2.91	-0.80	-0.16	1.28	**6.40**	-2.16	-0.87	0.62
RMW (SR)	0.18	-0.15	0.04	**0.29**	-0.28	-0.06	-0.01	0.14	**0.70**	-0.19	-0.08	0.06
CMA (alpha)	**0.37**	0.32	**0.33**	0.03	**0.28**	**0.50**	-0.01	**0.20**	0.21	**0.51**	-0.02	**0.57**
CMA (t-stat)	**2.69**	1.51	**2.63**	0.16	**2.19**	**2.73**	-0.04	**2.29**	1.57	**2.94**	-0.10	**3.67**
CMA (AR)	**3.78**	2.35	**3.32**	-0.59	**2.82**	**4.90**	-1.66	**1.97**	0.98	**5.26**	-1.14	**5.81**
CMA (SR)	**0.47**	0.18	**0.44**	-0.05	**0.29**	**0.41**	-0.11	**0.35**	0.10	**0.46**	-0.10	**0.58**
UMD (alpha)	**0.89**	**0.72**	**0.78**	**0.44**	**0.81**	**1.18**	-0.17	0.02	**1.16**	**0.61**	**0.90**	**1.14**
UMD (t-stat)	**4.74**	**3.45**	**5.17**	**2.44**	**3.67**	**5.13**	-0.55	0.15	**6.70**	**2.69**	**4.12**	**4.39**
UMD (AR)	**10.03**	**7.60**	**9.03**	**4.34**	**9.14**	**13.16**	-3.67	-0.21	**14.03**	**6.06**	**9.72**	**13.07**
UMD (SR)	**0.84**	**0.50**	**0.84**	**0.35**	**0.68**	**0.78**	-0.22	-0.02	**1.21**	**0.42**	**0.67**	**0.87**

Table 4.4.2:
Industry-specific diagnostics **(1992-2019)**, all the results reported are in percentage terms except for t-statistics. Alpha refers to single-factor market regression (CAPM framework). Columns show respective industry groups.

	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money	Other
SMB (alpha)	**-0.40**	-0.03	0.15	-0.23	-0.03	-0.19	-0.42	0.20	-0.11	-0.05	0.24	-0.01
SMB (t-stat)	**-2.17**	-0.13	0.91	-0.77	-0.15	-0.92	-1.74	1.64	-0.71	-0.17	1.73	-0.05
SMB (AR)	**-3.58**	-2.13	1.07	-1.11	0.13	-1.29	-2.85	2.53	-0.21	0.92	0.77	-0.09
SMB (SR)	**-0.28**	-0.13	0.09	-0.07	0.01	-0.09	-0.16	0.33	-0.02	0.05	0.08	-0.01
HML (alpha)	0.12	0.33	0.04	0.32	-0.01	0.43	0.05	**0.40**	-0.11	0.39	0.03	0.11
HML (t-stat)	0.59	1.14	0.20	1.18	-0.04	1.29	0.20	**2.55**	-0.45	1.50	0.20	0.43
HML (AR)	2.26	2.65	1.02	3.95	0.58	2.32	-0.57	**3.35**	-0.56	2.93	-0.51	-0.87
HML (SR)	0.20	0.16	0.09	0.25	0.03	0.17	-0.04	**0.38**	-0.05	0.22	-0.06	-0.07
RMW (alpha)	**0.52**	0.47	**0.55**	0.35	0.31	**0.62**	**0.76**	**0.27**	0.26	0.51	0.30	0.43
RMW (t-stat)	**3.94**	1.31	**3.55**	1.66	1.14	**1.99**	**2.62**	**2.40**	1.67	1.76	1.81	1.93
RMW (AR)	**4.03**	3.92	**4.14**	1.62	1.09	**2.81**	**4.12**	**2.16**	0.53	1.08	3.22	2.04
RMW (SR)	**0.42**	0.19	**0.39**	0.13	0.07	**0.18**	**0.22**	**0.33**	0.05	0.06	0.38	0.15
CMA (alpha)	-0.04	0.48	0.29	0.07	0.26	0.25	0.18	**0.28**	0.23	**0.42**	**0.22**	**0.40**
CMA (t-stat)	-0.30	**2.08**	1.91	0.33	1.24	1.44	0.62	**2.17**	1.73	**2.52**	**2.01**	**2.41**
CMA (AR)	-0.30	4.08	2.67	-0.88	2.71	1.65	0.99	**2.44**	2.34	**4.38**	**1.14**	**3.32**
CMA (SR)	-0.03	0.27	0.28	-0.06	0.20	0.16	0.06	**0.35**	0.28	**0.48**	**0.14**	**0.35**
UMD (alpha)	0.40	**0.65**	**0.56**	0.43	0.03	**0.67**	**0.81**	0.38	0.42	0.31	0.37	**0.81**
UMD (t-stat)	1.83	**2.18**	**2.22**	1.08	0.10	**2.35**	**1.97**	1.57	1.55	1.33	1.49	**3.00**
UMD (AR)	1.67	**2.91**	**4.16**	-0.64	-3.56	**5.29**	**4.63**	1.73	1.59	1.49	-0.36	**5.81**
UMD (SR)	0.12	**0.14**	**0.27**	-0.02	-0.18	**0.29**	**0.20**	0.12	0.09	0.10	-0.02	**0.33**

The overall results indicate that similar to the aggregate risk factors, the premiums in industry portfolios vary over time. The robustness of the practical implementation of industry-specific strategies is thus also highly questioned. Another general trend is that for SMB and HML portfolios, much of the alpha is driven by the early time periods, pre-publication of the aggregate market anomalies in the academic literature. Nonetheless, we do observe that for some of the industries the returns remain relatively consistent across time samples. Non-Durables SMB demonstrates a negative SMB effect, which is even stronger in the more recent timeframe. Utilities HML retains statistical significance, with a slightly higher alpha intercept. The rest of the HML portfolios, however, lose much of their initial premiums and even result in negative annualized returns for some of the industries. RMW industry premiums highly vary across time periods, confirming the prior observation that industry RMW are poorly performing long-short portfolios. Healthcare CMA strategy also retains its significance and delivers high annualized returns. As noted before, Telecoms CMA and Energy CMA perform quite poorly – which is confirmed with respect to different time frames. UMD strategies also lose much of their alpha performance and deliver surprisingly low annualized returns and Sharpe Ratios in the most recent sample. The explanation for this could be the publications of industry momentum research, as well as the wide popularization of the UMD strategies since the 1990s. Business Equipment and Manufacturing do however retain relatively strong performance in the recent time sample, compared to other industry sectors. Overall, the Sharpe ratios and returns of most strategies significantly drop over time, pointing towards the fact that as the aggregate anomalous returns decline, so do the industry long-short premiums. The aforementioned industry groups do exhibit some persistence of "industry effects" however, as their respective premiums remain comparatively higher than the rest of the industries, potentially showing that some industries are indeed structurally more prone to retain certain 'risk' premiums. However, the lack of persistence in delivering risk-adjusted alpha with respect to the market, combined with the rigid methodological definitions used for portfolio formation, do highlight that the implementation of these strategies is by no means robust.

4.5 Spanning regressions of industry portfolios

As an additional analysis, we perform a set of spanning regressions for each industry's factor portfolios, as well as for the aggregate data factors. We are examining whether five industry-specific factors hold significant explanatory power for the average returns of the sixth industry factor portfolio, in order to determine how different factors interact with each other. We first conduct the exercise with the aggregate market data and then repeat the process for each of our industry groups.

Table 4.5.1: Using five factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns. The factors are formed using the aggregate market dataset, rather than industry-specific groups. All of the factors are formed using the 2x3 bivariate sorts on Size and respective variables. All of the coefficients are expressed in percentage terms.

	Int	R_m - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_m - R_f								
Coef.	0.87		24.20	5.77	-33.40	-86.70	-12.80	0.25
t-Statistic	5.68		4.48	0.75	-4.39	-8.19	-3.46	
p-Value	0.00		0.00	0.45	0.00	0.00	0.00	
SMB								
Coef.	0.30	12.10		-7.23	-50.70	-11.00	3.39	0.22
t-Statistic	2.70	4.48		-1.34	-9.97	-1.40	1.29	
p-Value	0.01	0.00		0.18	0.00	0.16	0.20	
HML								
Coef.	0.09	1.48	-3.71		12.40	**97.50**	-12.10	0.52
t-Statistic	**1.09**	0.75	-1.34		3.20	**23.50**	-6.63	
p-Value	**0.28**	0.45	0.18		0.00	0.00	0.00	
RMW								
Coef.	0.36	-8.43	-25.60	12.20		-29.60	5.72	0.21
t-Statistic	4.65	-4.39	-9.97	3.20		-5.43	3.08	
p-Value	0.00	0.00	0.00	0.00		0.00	0.00	
CMA								
Coef.	0.20	-10.60	-2.68	46.40	-14.30		4.08	0.55
t-Statistic	3.73	-8.19	-1.40	23.50	-5.43		3.17	
p-Value	0.00	0.00	0.16	0.00	0.00		0.00	
UMD								
Coef.	0.71	-13.80	7.36	-51.20	24.50	36.30		0.10
t-Statistic	4.37	-3.46	1.29	-6.63	3.08	3.17		
p-Value	0.00	0.00	0.20	0.00	0.00	0.00		

As can be seen in the above table, the HML factor does not have a statistically significant intercept coefficient, implying that it is explained very well by the rest of the factors in the regressions. Indeed, it is explained to the largest extent by the CMA factor with a coefficient of 0.98 and a very strong t-stat of 23.5. Similarly, Fama-French (2015) find that the CMA factor yields a coefficient of 1.04 with a t-stat of 23.03 in their analysis spanning from year 1963 to year 2013, which together with the explanatory power of RMW, results in HML factor becoming redundant for the purpose of asset pricing tests. We thus confirm the findings of Fama-French with the most recent data sample.

We move on to the examination of within-industry spanning regressions, to see how the industry-specific factors interact with one another. We present the findings for the industry group 1, Non-Durables, in Table 4.4.2 below which we deem very representative of the overall trends across industries, and include the rest of the within-industry results in Appendix C.

Table 4.5.2: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Non-Durables*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Int	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - R_f								
Coef.	0.73		-9.32	4.60	-1.81	-10.35	-14.41	0.02
t-Statistic	4.29		-1.84	0.68	-0.23	-1.48	-3.26	
p-Value	0.00		0.07	0.50	0.82	0.14	0.00	
SMB								
Coef.	**0.13**	-5.42		-13.73	**-37.31**	2.31	-17.03	0.10
t-Statistic	**0.96**	-1.84		-2.67	**-6.49**	0.43	-5.11	
p-Value	**0.34**	0.07		0.01	**0.00**	0.67	0.00	
HML								
Coef.	0.49	1.49	-7.67		**-60.08**	**23.47**	-8.06	0.35
t-Statistic	5.12	0.68	-2.67		**-15.92**	**6.02**	-3.20	
p-Value	0.00	0.50	0.01		**0.00**	**0.00**	0.00	
RMW								
Coef.	0.42	-0.45	-15.91	-45.84		-3.10	-2.74	0.34
t-Statistic	5.02	-0.23	-6.49	-15.92		-0.89	-1.24	
p-Value	0.00	0.82	0.00	0.00		0.38	0.22	
CMA								
Coef.	**0.13**	-3.14	1.21	**21.93**	-3.80		0.30	0.09
t-Statistic	**1.39**	-1.48	0.43	**6.02**	-0.89		0.12	
p-Value	**0.17**	0.14	0.67	**0.00**	0.38		0.90	
UMD								
Coef.	0.69	-10.91	-22.17	-18.79	-8.38	0.75		0.07
t-Statistic	4.64	-3.26	-5.11	-3.20	-1.24	0.12		
p-Value	0.00	0.00	0.00	0.00	0.22	0.90		

We observe from the regression results that the excess industry returns are very poorly explained by most factors formed on companies only from the Non-Durables industry, as indicated by the R-squared of only 2% and low statistical significance of all factors other than UMD. This finding is contrary to the finding of Moerman (2005), as the industry factors we form show very little explanatory power for the industries' costs of equity. A notable exception is the Business Equipment group, where the R-squared is 31% (Appendix C, Table C6) – a relatively high explanatory power, similar to that achieved by the aggregate factors.

The more interesting finding is that the Non-Durables HML has very high coefficients on RMW and CMA factors, with very strong statistical significance. The slope on CMA factor is strongly positive, implying that high B/M stocks within Non-Durables tend to display return behavior consistent with stocks holding conservative investment policies. This is in line with the trend that we see on aggregate data. The slope on the RMW factor, however, is strongly negative, implying that the value stocks within the industry behave like stocks with weak profitability. This is different to the trend we see with aggregate data, but in line with what one might expect – lower valued companies are expected to be less profitable on average over a longer time horizon, if markets are pricing companies according to their profit-generating ability.

The strong relation between HML and CMA is also displayed in the industry-specific CMA regression results, where the positive slope on HML holds much explanatory power of the CMA factor, yielding an intercept that has no statistical significance. This is an important finding, because it implies that for an investor interested in Non-Durables industry group only, pursuing both HML and CMA strategies would be suboptimal as the underlying exposure is significantly correlated. Thus, rather than reaping premiums of both CMA and HML Non-Durables portfolio trades, the investor would to a large extent be loading onto the similar risk exposure, in terms of the average return movement of two anomalous premiums. Indeed, if value stocks overall do display lower levels of investment, the investor would effectively be undertaking trades in the same companies across two different "style" strategies. In the case of Non-Durables, pursuing the HML industry factor strategy would be a more optimal choice, as this trade yields higher returns and higher alpha than CMA, with similar return behavior.

The second trend we notice is the relation between the SMB and RMW industry-specific factors. The RMW slope is strongly negative, implying that small-sized stocks tend to display the same behavior as stocks of weak operating profitability. After accounting for the rest of the factors and the high factor loading on RMW, the Non-Durables SMB factor appears to be explained to a large extent. Again, the potential implications of this are that Non-Durables factor trades constructed on RMW appear to be a more optimal choice to SMB-focused trades, especially if RMW industry-specific trades show higher returns – which in the time sample that we study, they do. This is also consistent with the previous finding that Non-Durables SMB actually delivers a negative alpha, with relatively strong statistical significance across time samples.

We present the rest of the spanning regression results in Appendix C. While the results do differ from industry to industry, the general trend of high relation between SMB and RMW, as well as between HML on one side and CMA and RMW on the other, appear for all of the industries. Indeed, for four of the industries the CMA factor loses statistical significance of the intercept due to its HML exposure: Energy, Chemicals, Telecoms and Utilities. HML shows signs of potential redundancy in only two industry groups, Telecoms and Other, due to significant exposures to other industry-specific portfolios. This result is expected for the Other industry group, as it very much coincides with the aggregate data results. However, the Telecoms effect is a useful insight for Telecoms-focused investors. SMB factor's intercept exhibits low statistical significance for all but three of the industries: Durables, Manufacturing and Utilities, after other industry-specific factors are accounted for. This points towards previous findings that the SMB factor has weaker anomalous average return effects, which seems to especially hold within industries. Lastly, we notice exposures of industry-specific UMD with HML, RMW and CMA factors for different industries. However, the explanatory power of other factors yields the UMD intercept coefficient insignificant only for two of the industry groups: Utilities and Telecoms. This finding could be somewhat expected, however, considering that it is exactly these two industries that show the lowest levels of UMD effects both in the excess market and respective aggregate factor regressions.

The conclusion of the spanning regression analysis is that even within industries, factors exhibit significant degrees of co-movement and thereby potentially offer similar risk exposures, in terms of the return covariation of the constructed long-short industry portfolios. This inference could be driven by the mechanical construction of the portfolios, i.e. if value stocks in most cases do exhibit low level of investment, the likelihood is that same companies will be included in both the HML and CMA industry portfolios following the within-industry bivariate sorting process. Alternatively, if the companies included in the portfolios differ – stocks sorted on the B/M and INV variables exhibit similar return behavior, making the different styles of factor investing potentially exposed to the same underlying risk. The implication of this is that an investor seeking single-industry exposure would make a suboptimal choice by pursuing multiple factor style strategies that exhibit mutually correlated return behavior.

5 Discussion

In the methodology that we apply we remain rather strict with the definitions of industries and the portfolio sorting procedures we use with the aim of replicating the methodology of Fama-French as close as possible in order to have consistent and comparable metrics with respect to the established aggregate risk factors. However, this approach has its limitations. Firstly, the use of unconditional sorting procedure leaves most sub-portfolios highly skewed towards Small companies, in terms of the number of firms said portfolios are composed of. This is further exacerbated by the use of NYSE breakpoints for the median calculations, as the average NYSE stock's market capitalization is significantly higher than that of the average AMEX and NASDAQ stock. While in the aggregate dataset such differentiation does not significantly impact the sub-portfolio formation; in the industry portfolios it leads to undiversified portfolios of Big companies, especially in the early time sample of the study. Considering we use value-weighted returns of the sub-portfolios, this means that several large-cap companies dominate the return patterns of these portfolios. Moreover, it also leads to below-median NYSE companies significantly influencing the return patterns of the Small portfolios, as they are for the large part significantly bigger than most AMEX and NASDAQ companies. The end result of this is high co-movement of industry portfolio returns with the aggregate factor portfolio returns. The application of conditional sorting procedures and different sorting variables, rather than focusing on Size as a mandatory variable in the bivariate sorting process, would likely yield somewhat different results.

Considering the fact that observed within-industry anomalous premiums vary over time, we also believe that further analysis on the optimal holding periods when implementing industry-specific strategies would be a great extension to the research. Analyzing the strategies over different entry and exit points of historical business cycles, for example, might provide inferences about optimal market timing. Perhaps, when the market is on a bull run, certain strategies such as the value anomaly will underperform the market, and when the market is in a slump period said strategy will beat the market. The extent of this variation might also be industry-dependent, which is why an investor seeking to exploit the value anomaly might want to switch between industries of focus dependent on the stage of the business cycle. Moreover, it would be interesting to examine the predictability of the long-short portfolio return time-series in the dynamic lead-lag framework, as has been done with the aggregate factors. Further research in this area, accounting for limitations we identify above, could be very value-additive to the academic literature.

Furthermore, estimation of trading costs for anomaly-based strategies would be beneficial for the practical implementation of some of the findings. This could be done by estimating the average turnover during the portfolio rebalancing period in the portfolio sorting process. Another contribution to the literature could be done by examining the performance of long-only strategies, as opposed to the long-short strategies we have analyzed. Such research would analyze the performance of strategies that take a long position in small, low book-to-market, high operating profitability, lower investment and high “momentum” returns, without financing them through a short position in their counterpart portfolios. We direct the focus towards the long-short premiums intentionally, as such strategies are designed to have low market beta loadings, allowing for better isolation of the anomalous effects.

Lastly, the research could be further extended by examining the performance of other, lesser-known anomalies that have been recently put forward in the academic literature. As McLean and Pontiff (2013) point out, many asset pricing anomalies suffer from post-publication decay of average returns, whereby the publishing of academic literature potentially leads to premiums being arbitraged away by aware investors. Thus, focus on more recent anomalies, using the industry-specific methodology, might show higher return premiums to be earned than is shown with the already established anomalies we have analyzed. Potential examples, already studied by Fama and French on aggregate market data, are accruals, net share issues, and market beta anomalies.

6 Conclusion

The primary research question of this thesis is to determine whether the patterns of anomalous average returns observed in the U.S. stocks persist within industry subsets of the market. We find comprehensive evidence that the patterns do follow the same general trends. Small companies in each industry on average deliver higher returns than Big companies, with Non-Durables industry group being a notable exception. Likewise, high B/M stocks on average deliver higher returns than low B/M stocks in all industries. Firms with robust operating profitability deliver higher average returns than firms with weak operating profitability in most industries. Notable exceptions here are Healthcare and Chemicals industry groups, where the profitability premiums are rather flat, but nonetheless positive. Industry-grouped stocks of companies with conservative investment policies also on average outperform industry-grouped stocks of companies with aggressive investment policies, with the exceptions of Telecoms and Energy where the premiums are relatively flat. Lastly, within-industry one-year momentum effect is highly present across all industries, with largely strong statistical significance.

The second research question examines the viability of industry-specific factor strategies in terms of their risk-adjusted performance. Indeed, we find evidence of differing magnitudes of long-short spreads for each industry, some of which remain unexplained by the FF5 and Momentum risk premia over the observed time sample. We find that industry SMB trades perform rather poorly, even with respect to market, which is consistent with the performance of said trades formed on the aggregate data. For the rest of the industry portfolios, long-short premiums largely perform well with respect to the historical market premium but are overall strongly explained by the aggregate Fama-French risk factors. We thus do not find evidence of systemic presence of above-average risk-adjusted returns in the industry-sorted factor portfolios. Moreover, we also find that the long-short industry portfolio spreads vary over time and fail to deliver a persistent risk-adjusted alpha over different time samples. Additionally, the reported outperformance of several industry portfolios, which seems to be largely driven by the early data periods, overall does not exhibit surprisingly high Sharpe ratios or risk-adjusted alphas, even without accounting for trading costs, taxes and similar frictions. All of this implies that the viability of industry-sorted strategies remains questionable, and that their potential superiority compared to anomaly-based strategies formed on aggregate market data cannot be confirmed.

Lastly, we show evidence of shared risk exposures for some of the industry-formed portfolios, in terms of their average monthly return movement. We find that different industries display different factor relations, but that some general trends emerge. Across most industries, using our methodology and applied industry classifications, there is evidence of high relation and explanatory power between industry-specific SMB and RMW, as well as between HML on one side and CMA and RMW on the other. Both of the relationships are well-observed in the academic literature on the aggregate Fama-French factors and seem to translate to within-industry sets of companies. The SMB and RMW relationship is negative, implying that small-sized stocks within industries tend to display the same behavior as stocks of weak operating profitability. The HML and CMA relationship is positive, similarly implying that industry-sorted high B/M stocks tend to do little investment. However, contrary to the findings on the aggregate data, the HML and RMW slopes are strongly negative across most industries. The implication of this is that high B/M value stocks behave like stocks with weak profitability within industries. In terms of practical inferences, this finding suggests that an investor seeking single-industry exposure would make a suboptimal choice by pursuing multiple factor style strategies that exhibit mutually correlated return behavior in the same direction, as this would effectively lead to pursuing premiums with same underlying risk, in terms of return co-movement.

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Appendices

Appendix A: *Yearly number of unique companies per industry group*

Year	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money	Other
1963	259	113	531	119	103	130	25	111	219	39	142	247
1964	275	116	543	119	106	140	29	111	237	40	144	252
1965	289	115	549	113	109	150	30	114	247	43	148	256
1966	293	115	559	111	109	155	32	116	248	42	152	255
1967	290	121	577	113	109	169	35	117	251	47	146	254
1968	288	116	562	108	108	188	30	123	260	52	153	265
1969	294	123	545	109	108	195	34	124	274	57	168	286
1970	307	122	550	113	105	196	35	131	286	62	184	297
1971	325	126	543	117	105	192	36	134	310	76	208	310
1972	605	223	983	222	159	475	65	196	681	181	930	751
1973	609	226	1001	228	159	505	67	195	697	192	969	770
1974	558	209	944	231	149	471	64	196	646	179	897	665
1975	526	189	932	237	151	450	62	195	633	179	869	621
1976	524	187	930	252	148	472	63	195	633	178	870	618
1977	500	181	906	259	144	471	64	198	630	185	890	613
1978	478	175	885	260	133	484	66	199	617	171	902	618
1979	445	171	838	287	129	505	68	197	589	181	911	601
1980	423	161	833	382	128	540	77	204	582	204	920	619
1981	409	167	848	492	138	632	82	205	595	237	914	716
1982	396	155	826	504	136	676	82	204	585	254	922	735
1983	394	166	835	495	140	863	95	208	675	350	1026	757
1984	407	172	843	467	142	938	118	202	709	390	1072	798
1985	386	182	816	413	142	988	125	203	707	406	1148	792
1986	391	186	813	365	144	1029	138	202	751	461	1343	861
1987	396	184	799	306	151	1045	146	197	773	483	1444	877
1988	390	181	783	283	148	1025	154	199	745	500	1456	855
1989	366	164	736	268	142	991	153	194	689	496	1401	812
1990	336	160	691	275	129	954	147	195	663	509	1365	798
1991	354	155	670	274	129	938	146	193	680	583	1299	784
1992	362	158	677	272	133	972	148	196	718	651	1323	781
1993	385	183	718	277	134	1038	165	192	788	677	1385	828
1994	392	204	756	283	142	1110	184	193	852	713	1434	894
1995	401	211	776	278	150	1240	200	191	887	734	1466	948
1996	406	212	787	281	156	1418	222	191	932	799	1507	1029
1997	420	206	771	281	143	1530	233	194	931	819	1500	1071
1998	402	197	744	262	143	1510	230	180	886	790	1489	1058
1999	375	182	693	244	132	1556	254	168	838	727	1387	1017
2000	341	166	632	219	126	1598	261	157	765	690	1283	983
2001	297	147	568	212	110	1438	233	130	674	650	1182	867
2002	264	134	525	190	101	1227	195	124	604	622	1104	755
2003	258	124	480	178	94	1091	166	117	579	598	1071	702
2004	244	121	453	178	93	1006	162	118	544	615	1059	673
2005	242	120	443	191	98	972	169	118	522	620	1027	661
2006	230	109	431	196	104	917	167	120	506	619	1027	657
2007	225	106	414	203	108	894	156	120	479	625	1037	673
2008	217	104	398	198	100	815	151	115	434	586	979	646
2009	205	103	379	195	95	745	137	109	408	532	907	649
2010	198	91	366	186	90	701	121	106	388	482	842	694
2011	191	89	352	182	85	647	112	105	370	441	788	721
2012	181	83	336	176	81	610	104	100	357	414	749	753
2013	172	81	321	170	82	582	107	93	340	387	717	848
2014	166	74	311	168	84	557	100	93	339	382	703	986
2015	161	74	305	160	80	541	92	96	328	367	682	1081
2016	156	73	290	149	82	500	89	93	319	348	651	1111
2017	145	69	283	152	80	460	78	84	317	327	620	1184
2018	140	70	276	150	76	437	73	81	300	312	589	1278
2019	137	68	269	139	70	411	71	76	292	295	560	1291

Appendix B: *Comparison statistics of Calculated vs Posted Industry Returns*

Figure B.1: The group of charts represents a comparison of the cumulative equal-weighted returns (in percentage terms) between the calculated and posted industry portfolios. *Calculated* returns are constructed following the described methodology and industry classification within this thesis, while *Posted* returns are downloaded from Kenneth French's website.

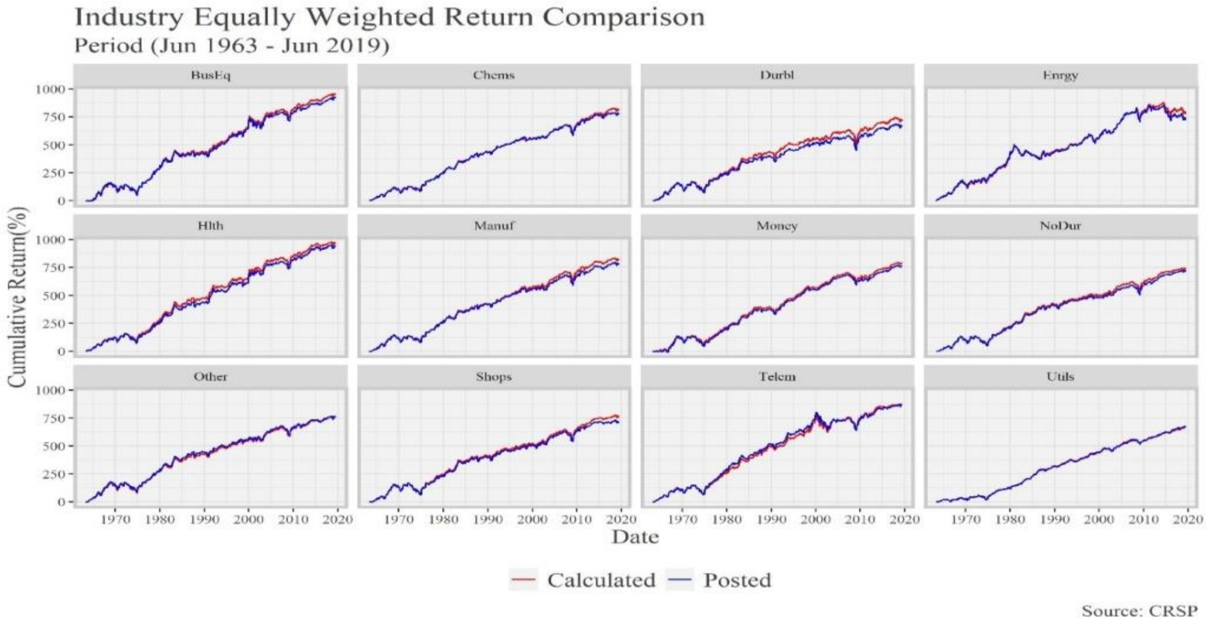


Figure B.2: The group of charts represents a comparison of the cumulative value-weighted returns (in percentage terms) between the calculated and posted industry portfolios. *Calculated* returns are constructed following the described methodology and industry classification within the thesis, while *Posted* returns are downloaded from Fama-French website.

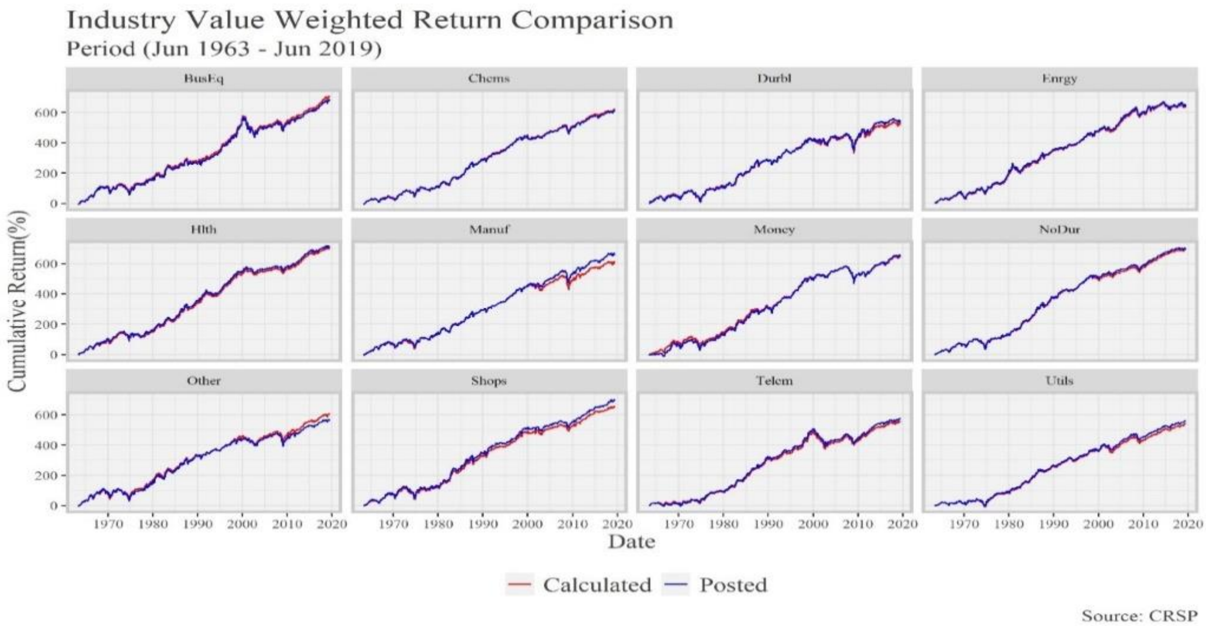


Table B.1: The table summarizes the comparison return statistics for the Calculated and Posted returns presented in **Figure B.1** and **Figure B.2.** Apart from the correlation results, everything is presented in percentage terms.

	Equally Weighted				Value Weighted			
	Correlation	Mean Calc	Mean Posted	Difference	Correlation	Mean Calc	Mean Posted	Difference
NoDur	0.99	1.10	1.07	0.03	0.99	1.04	1.05	-0.01
Durbl	0.99	1.08	1.00	0.08	0.98	0.79	0.82	-0.02
Manuf	1.00	1.23	1.17	0.06	0.98	0.91	1.00	-0.08
Enrgy	0.99	1.16	1.08	0.08	1.00	0.96	0.97	-0.01
Chems	0.98	1.22	1.16	0.06	0.99	0.93	0.91	0.02
BusEq	1.00	1.42	1.38	0.05	1.00	1.05	1.02	0.04
Telcm	0.98	1.30	1.28	0.01	0.98	0.83	0.86	-0.03
Utils	0.99	1.00	1.01	-0.01	1.00	0.81	0.84	-0.03
Shops	1.00	1.14	1.06	0.08	0.99	0.98	1.04	-0.07
Hlth	0.99	1.44	1.39	0.05	0.99	1.05	1.07	-0.02
Money	1.00	1.18	1.14	0.04	0.99	0.96	0.98	-0.01
Other	0.99	1.13	1.14	0.00	0.97	0.90	0.85	0.06

Figure B.3: The group of charts represents a comparison of the cumulative returns between the calculated and reported Fama-French aggregate factors. *Calculated* returns are constructed following the described methodology, while *Reported* returns are downloaded from Kenneth French's website.

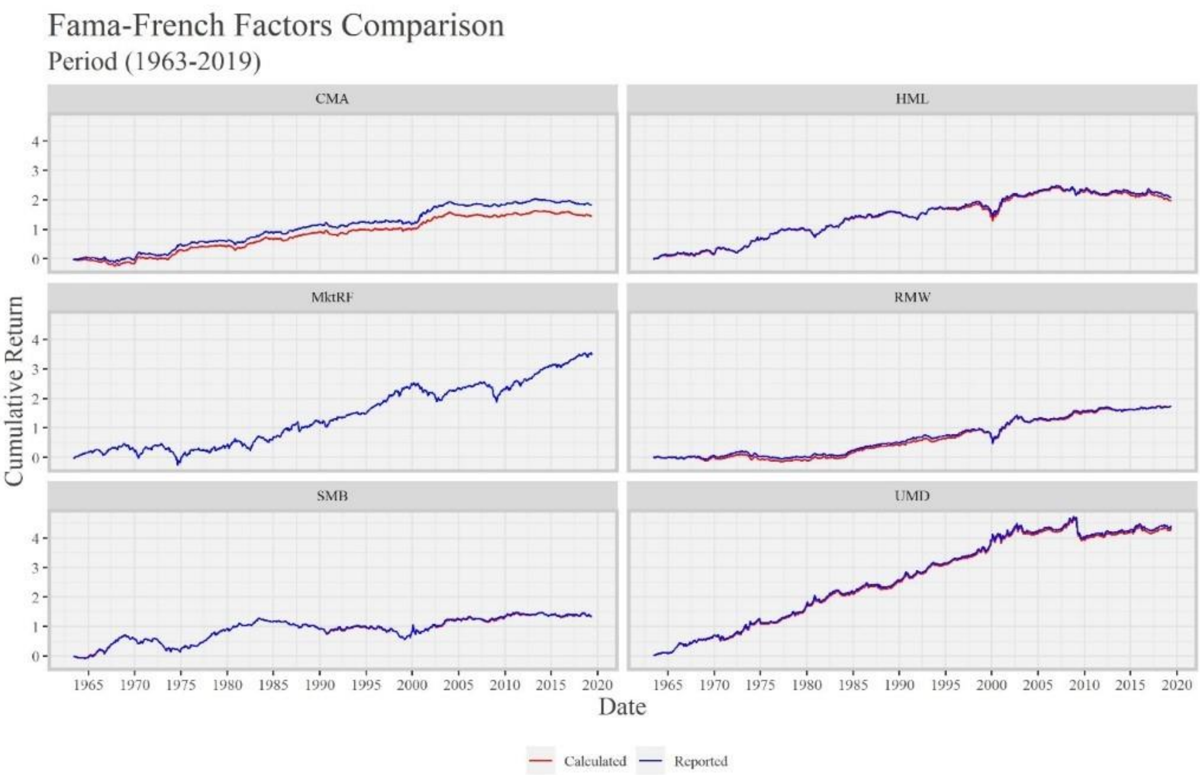


Table B.2: The table summarizes the comparison return statistics for the Calculated and Reported factor returns presented in *Figure B.3*

Factor	Correlation	Mean Calc	Mean Reported	Difference
Market	1.00	0.53	0.53	0.00
SMB	1.00	0.20	0.20	0.00
HML	0.98	0.29	0.31	-0.02
RMW	0.98	0.26	0.26	0.00
CMA	0.98	0.22	0.27	-0.06
UMD	1.00	0.64	0.65	-0.01

Appendix C: Spanning regressions of industry portfolios

Table C.1: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Non-Durables*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - R_f								
Coef.	0.73		-9.32	4.60	-1.81	-10.35	-14.41	0.02
t-Statistic	4.29		-1.23	0.50	-0.19	-1.27	-1.87	
p-Value	0.00		0.22	0.62	0.85	0.20	0.06	
SMB								
Coef.	0.13	-5.42		-13.73	-37.31	2.31	-17.03	0.10
t-Statistic	0.88	-1.16		-1.45	-4.49	0.32	-3.49	
p-Value	0.38	0.25		0.15	0.00	0.75	0.00	
HML								
Coef.	0.49	1.49	-7.67		-60.08	23.47	-8.06	0.35
t-Statistic	5.24	0.51	-1.49		-12.18	4.89	-2.28	
p-Value	0.00	0.61	0.14		0.00	0.00	0.02	
RMW								
Coef.	0.42	-0.45	-15.91	-45.84		-3.10	-2.74	0.34
t-Statistic	5.57	-0.20	-4.51	-13.44		-0.79	-1.07	
p-Value	0.00	0.84	0.00	0.00		0.43	0.28	
CMA								
Coef.	0.13	-3.14	1.21	21.93	-3.80		0.30	0.09
t-Statistic	1.44	-1.31	0.34	5.35	-0.80		0.09	
p-Value	0.15	0.19	0.73	0.00	0.43		0.93	
UMD								
Coef.	0.69	-10.91	-22.17	-18.79	-8.38	0.75		0.07
t-Statistic	4.82	-1.60	-2.97	-1.96	-1.13	0.09		
p-Value	0.00	0.11	0.00	0.05	0.26	0.93		

Table C.2: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Durables*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - Rf								
Coef.	0.62		-23.16	2.96	11.22	-5.11	-29.67	0.11
t-Statistic	2.39		-3.03	0.28	1.80	-0.65	-3.79	
p-Value	0.02		0.00	0.78	0.07	0.52	0.00	
SMB								
Coef.	0.44	-9.05		-37.88	-19.09	-10.11	4.00	0.22
t-Statistic	3.02	-2.94		-7.36	-4.06	-2.25	0.91	
p-Value	0.00	0.00		0.00	0.00	0.02	0.36	
HML								
Coef.	0.51	1.15	-37.58		-21.11	9.45	-10.10	0.23
t-Statistic	3.24	0.29	-7.25		-4.91	1.93	-2.12	
p-Value	0.00	0.78	0.00		0.00	0.05	0.03	
RMW								
Coef.	0.40	6.14	-26.72	-29.79		-16.32	-1.68	0.12
t-Statistic	2.26	1.56	-4.85	-4.93		-2.51	-0.23	
p-Value	0.02	0.12	0.00	0.00		0.01	0.82	
CMA								
Coef.	0.41	-2.14	-10.83	10.20	-12.49		-5.18	0.07
t-Statistic	2.61	-0.64	-2.21	1.98	-1.76		-0.89	
p-Value	0.01	0.52	0.03	0.05	0.08		0.37	
UMD								
Coef.	0.74	-19.21	6.62	-16.87	-1.99	-8.02		0.11
t-Statistic	4.38	-3.05	0.84	-1.89	-0.21	-0.89		
p-Value	0.00	0.00	0.40	0.06	0.84	0.37		

Table C.3: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Manufacturing*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - Rf	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - Rf								
Coef.	0.86		-4.68	3.15	-45.06	-42.89	-18.88	0.09
t-Statistic	3.94		-0.55	0.19	-4.40	-4.35	-2.20	
p-Value	0.00		0.58	0.85	0.00	0.00	0.03	
SMB								
Coef.	0.26	-1.73		-27.24	-25.30	12.30	0.49	0.06
t-Statistic	2.02	-0.54		-2.53	-3.46	1.47	0.10	
p-Value	0.04	0.59		0.01	0.00	0.14	0.92	
HML								
Coef.	0.42	0.71	-16.75		-46.10	36.53	-11.33	0.39
t-Statistic	4.18	0.18	-2.65		-9.26	4.82	-2.21	
p-Value	0.00	0.86	0.01		0.00	0.00	0.03	
RMW								
Coef.	0.46	-8.77	-13.36	-39.57		-16.65	-0.41	0.33
t-Statistic	4.76	-4.06	-3.83	-10.11		-2.91	-0.10	
p-Value	0.00	0.00	0.00	0.00		0.00	0.92	
CMA								
Coef.	0.26	-7.82	6.09	29.39	-15.60		-3.10	0.25
t-Statistic	2.58	-3.62	1.57	6.33	-3.10		-0.90	
p-Value	0.01	0.00	0.12	0.00	0.00		0.37	
UMD								
Coef.	0.77	-9.85	0.70	-26.08	-1.11	-8.88		0.08
t-Statistic	4.89	-2.08	0.09	-2.30	-0.09	-0.84		
p-Value	0.00	0.04	0.93	0.02	0.93	0.40		

Table C.4: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Energy*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - Rf	SMB	HML	RMW	CMA	UMD	R2
R_{ind} - Rf								
Coef.	0.67		32.10	-2.15	-21.52	-15.34	-9.66	0.12
t-Statistic	3.53		4.60	-0.28	-3.06	-2.42	-2.01	
p-Value	0.00		0.00	0.78	0.00	0.02	0.04	
SMB								
Coef.	0.02	16.50		4.82	-30.69	-17.01	-8.10	0.18
t-Statistic	0.15	4.08		0.90	-4.81	-2.82	-1.89	
p-Value	0.88	0.00		0.37	0.00	0.00	0.06	
HML								
Coef.	0.70	-1.16	5.08		-18.19	20.25	-14.14	0.09
t-Statistic	4.61	-0.29	0.97		-2.27	3.08	-1.43	
p-Value	0.00	0.78	0.33		0.02	0.00	0.15	
RMW								
Coef.	0.35	-6.76	-18.75	-10.57		-9.27	-7.14	0.12
t-Statistic	2.82	-2.92	-5.49	-2.04		-2.01	-2.10	
p-Value	0.00	0.00	0.00	0.04		0.04	0.04	
CMA								
Coef.	-0.03	-7.02	-15.15	17.14	-13.51		7.33	0.10
t-Statistic	-0.24	-2.13	-3.03	2.66	-1.94		1.71	
p-Value	0.81	0.03	0.00	0.01	0.05		0.09	
UMD								
Coef.	0.68	-11.15	-18.20	-30.18	-26.24	18.48		0.10
t-Statistic	3.03	-1.65	-1.59	-1.31	-1.81	1.45		
p-Value	0.00	0.10	0.11	0.19	0.07	0.15		

Table C.5: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Chemicals*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - R_f								
Coef.	0.56		-2.61	9.92	7.82	-8.08	-7.69	0.02
t-Statistic	3.08		-0.39	1.40	1.18	-1.05	-1.53	
p-Value	0.00		0.70	0.16	0.24	0.29	0.13	
SMB								
Coef.	0.24	-1.65		-19.24	-13.07	17.67	-0.38	0.05
t-Statistic	1.74	-0.40		-2.52	-2.16	3.11	-0.09	
p-Value	0.08	0.69		0.01	0.03	0.00	0.93	
HML								
Coef.	0.38	5.62	-17.16		-47.38	27.02	-11.50	0.30
t-Statistic	2.58	1.29	-2.42		-7.25	5.19	-1.70	
p-Value	0.01	0.20	0.02		0.00	0.00	0.09	
RMW								
Coef.	0.20	4.34	-11.42	-46.41		3.28	-7.10	0.23
t-Statistic	1.31	1.11	-2.68	-8.84		0.46	-1.21	
p-Value	0.19	0.27	0.01	0.00		0.64	0.23	
CMA								
Coef.	0.18	-4.15	14.30	24.52	3.04		-1.31	0.10
t-Statistic	1.41	-1.05	2.71	5.34	0.45		-0.46	
p-Value	0.16	0.29	0.01	0.00	0.65		0.64	
UMD								
Coef.	0.49	-8.54	-0.67	-22.57	-14.23	-2.83		0.04
t-Statistic	2.91	-1.34	-0.09	-1.45	-1.04	-0.42		
p-Value	0.00	0.18	0.93	0.15	0.30	0.67		

Table C.6: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Business Equipment*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - Rf								
Coef.	1.12		-2.17	-43.49	-69.42	-33.49	-0.46	0.31
t-Statistic	4.95		-0.31	-4.93	-8.96	-3.31	-0.08	
p-Value	0.00		0.76	0.00	0.00	0.00	0.94	
SMB								
Coef.	0.20	-0.96		-19.38	-43.48	4.96	-2.30	0.22
t-Statistic	1.37	-0.31		-3.69	-6.45	0.77	-0.42	
p-Value	0.17	0.76		0.00	0.00	0.44	0.68	
HML								
Coef.	0.55	-16.29	-16.40		-17.52	44.89	-9.94	0.30
t-Statistic	3.73	-4.05	-3.80		-2.64	7.41	-2.72	
p-Value	0.00	0.00	0.00		0.01	0.00	0.01	
RMW								
Coef.	0.46	-26.61	-37.66	-17.94		-13.71	4.29	0.35
t-Statistic	2.91	-5.83	-6.43	-2.18		-1.85	0.80	
p-Value	0.00	0.00	0.00	0.03		0.06	0.43	
CMA								
Coef.	0.21	-9.20	3.08	32.91	-9.82		4.77	0.24
t-Statistic	1.68	-3.57	0.79	6.02	-1.99		1.23	
p-Value	0.09	0.00	0.43	0.00	0.05		0.22	
UMD								
Coef.	0.91	-0.39	-4.44	-22.68	9.57	14.84		0.03
t-Statistic	4.90	-0.08	-0.42	-2.88	0.87	1.24		
p-Value	0.00	0.94	0.68	0.00	0.39	0.21		

Table C.7: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Telecoms*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	$R_{ind} - R_f$	SMB	HML	RMW	CMA	UMD	R^2
$R_{ind} - R_f$								
Coef.	0.57		-5.24	-17.40	-10.83	3.41	-10.76	0.05
t-Statistic	2.88		-0.89	-2.40	-1.91	0.76	-1.83	
p-Value	0.00		0.37	0.02	0.06	0.45	0.07	
SMB								
Coef.	0.28	-4.86		-9.53	-30.24	-2.15	-0.38	0.11
t-Statistic	1.52	-0.93		-1.59	-4.97	-0.32	-0.08	
p-Value	0.13	0.35		0.11	0.00	0.75	0.94	
HML								
Coef.	0.22	-14.51	-8.57		-24.77	20.06	2.54	0.13
t-Statistic	1.22	-2.54	-1.62		-4.82	3.66	0.64	
p-Value	0.22	0.01	0.11		0.00	0.00	0.52	
RMW								
Coef.	0.45	-11.48	-34.58	-31.49		8.82	12.10	0.19
t-Statistic	2.36	-2.42	-6.22	-5.83		1.53	2.96	
p-Value	0.02	0.02	0.00	0.00		0.13	0.00	
CMA								
Coef.	0.14	2.95	-2.01	20.80	7.19		-11.72	0.07
t-Statistic	0.74	0.76	-0.32	3.46	1.30		-1.65	
p-Value	0.46	0.45	0.75	0.00	0.19		0.10	
UMD								
Coef.	0.33	-16.54	-0.63	4.68	17.53	-20.82		0.07
t-Statistic	1.48	-1.78	-0.08	0.63	2.53	-1.63		
p-Value	0.14	0.08	0.94	0.53	0.01	0.10		

Table C.8: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Utilities*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - R_f								
Coef.	0.69		-71.48	-13.36	-17.25	-19.47	-15.19	0.17
t-Statistic	4.76		-7.04	-1.29	-1.96	-1.96	-2.01	
p-Value	0.00		0.00	0.20	0.05	0.05	0.04	
SMB								
Coef.	0.25	-15.61		6.77	-6.21	-3.28	5.73	0.15
t-Statistic	4.22	-5.29		1.34	-1.22	-0.62	1.89	
p-Value	0.00	0.00		0.18	0.22	0.53	0.06	
HML								
Coef.	0.30	-3.52	8.17		-59.60	41.93	6.49	0.41
t-Statistic	3.85	-1.21	1.30		-8.48	5.39	1.83	
p-Value	0.00	0.23	0.19		0.00	0.00	0.07	
RMW								
Coef.	0.29	-4.01	-6.61	-52.59		18.55	17.53	0.39
t-Statistic	3.86	-1.83	-1.29	-8.70		3.07	4.46	
p-Value	0.00	0.07	0.20	0.00		0.00	0.00	
CMA								
Coef.	0.10	-4.01	-3.10	32.78	16.43		-0.32	0.16
t-Statistic	1.41	-2.03	-0.63	6.54	3.04		-0.09	
p-Value	0.16	0.04	0.53	0.00	0.00		0.93	
UMD								
Coef.	-0.01	-11.58	19.99	18.76	57.46	-1.17		0.15
t-Statistic	-0.09	-1.88	1.69	1.79	4.13	-0.09		
p-Value	0.93	0.06	0.09	0.07	0.00	0.93		

Table C.9: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Shops*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - R_f								
Coef.	0.86		13.90	-11.05	-17.32	-54.76	-16.51	0.13
t-Statistic	4.85		1.39	-1.04	-2.02	-6.02	-2.84	
p-Value	0.00		0.17	0.30	0.04	0.00	0.00	
SMB								
Coef.	0.14	6.00		10.41	-11.58	-23.83	-2.75	0.07
t-Statistic	1.10	1.50		1.64	-1.89	-3.19	-0.65	
p-Value	0.27	0.13		0.10	0.06	0.00	0.52	
HML								
Coef.	0.31	-3.06	6.68		-46.57	38.34	-18.63	0.45
t-Statistic	2.70	-1.06	1.50		-9.81	6.29	-3.30	
p-Value	0.01	0.29	0.13		0.00	0.00	0.00	
RMW								
Coef.	0.41	-4.49	-6.95	-43.54		-10.08	-1.00	0.31
t-Statistic	4.64	-2.10	-1.78	-10.45		-1.63	-0.27	
p-Value	0.00	0.04	0.07	0.00		0.10	0.79	
CMA								
Coef.	0.23	-12.86	-12.97	32.50	-9.14		2.99	0.30
t-Statistic	2.50	-6.35	-3.12	7.93	-1.60		0.98	
p-Value	0.01	0.00	0.00	0.00	0.11		0.33	
UMD								
Coef.	0.83	-11.91	-4.60	-48.51	-2.80	9.19		0.14
t-Statistic	5.45	-2.54	-0.59	-2.72	-0.27	0.92		
p-Value	0.00	0.01	0.55	0.01	0.78	0.36		

Table C.10: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Healthcare*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - R_f								
Coef.	0.85		-3.35	-27.64	-20.44	-4.21	-5.43	0.08
t-Statistic	4.87		-0.40	-3.86	-2.84	-0.68	-1.02	
p-Value	0.00		0.69	0.00	0.00	0.50	0.31	
SMB								
Coef.	0.30	-2.53		-18.08	-64.58	-8.02	4.61	0.36
t-Statistic	1.79	-0.38		-1.78	-4.75	-1.24	0.77	
p-Value	0.07	0.70		0.08	0.00	0.21	0.44	
HML								
Coef.	0.52	-17.67	-15.32		-10.45	22.22	-17.03	0.15
t-Statistic	3.40	-4.83	-1.78		-1.97	3.53	-3.10	
p-Value	0.00	0.00	0.08		0.05	0.00	0.00	
RMW								
Coef.	0.25	-12.13	-50.81	-9.70		-1.56	-3.44	0.35
t-Statistic	1.89	-3.56	-5.49	-1.78		-0.28	-0.58	
p-Value	0.06	0.00	0.00	0.08		0.78	0.56	
CMA								
Coef.	0.36	-1.70	-4.30	14.05	-1.06		2.05	0.05
t-Statistic	3.28	-0.68	-1.13	3.34	-0.27		0.62	
p-Value	0.00	0.50	0.26	0.00	0.79		0.54	
UMD								
Coef.	0.52	-4.64	5.23	-22.79	-4.97	4.34		0.05
t-Statistic	3.61	-1.05	0.81	-2.81	-0.65	0.60		
p-Value	0.00	0.30	0.42	0.01	0.52	0.55		

Table C.11: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Money(Financials)*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - R_f								
Coef.	0.86		-4.68	3.15	-45.06	-42.89	-18.88	0.16
t-Statistic	3.94		-0.55	0.19	-4.40	-4.35	-2.20	
p-Value	0.00		0.58	0.85	0.00	0.00	0.03	
SMB								
Coef.	0.15	-12.15		6.63	-16.74	-4.68	5.65	0.08
t-Statistic	1.27	-3.41		0.79	-2.35	-0.57	1.39	
p-Value	0.20	0.00		0.43	0.02	0.57	0.16	
HML								
Coef.	0.25	5.52	4.65		-19.08	44.36	-9.18	0.31
t-Statistic	2.36	2.25	0.79		-4.02	5.15	-2.39	
p-Value	0.02	0.02	0.43		0.00	0.00	0.02	
RMW								
Coef.	0.23	-3.82	-14.39	-23.38		-18.28	5.18	0.17
t-Statistic	2.17	-1.12	-2.29	-3.23		-2.30	1.10	
p-Value	0.03	0.26	0.02	0.00		0.02	0.27	
CMA								
Coef.	0.01	-9.89	-3.34	45.09	-15.16		7.10	0.29
t-Statistic	0.08	-3.05	-0.53	7.69	-1.97		1.72	
p-Value	0.94	0.00	0.59	0.00	0.05		0.09	
UMD								
Coef.	0.64	-20.83	11.69	-27.08	12.47	20.60		0.13
t-Statistic	3.41	-2.88	1.12	-2.73	1.03	1.38		
p-Value	0.00	0.00	0.26	0.01	0.31	0.17		

Table C.12: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Other Industries*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - R_f								
Coef.	0.88		10.17	-11.92	-14.97	-46.09	-13.40	0.10
t-Statistic	4.01		1.16	-1.31	-1.92	-4.39	-1.98	
p-Value	0.00		0.25	0.19	0.05	0.00	0.05	
SMB								
Coef.	0.23	3.48		-19.12	-14.08	7.85	-7.75	0.08
t-Statistic	1.82	1.18		-2.31	-1.58	1.08	-1.60	
p-Value	0.07	0.24		0.02	0.11	0.28	0.11	
HML								
Coef.	0.19	-3.93	-18.43		9.98	51.38	-14.88	0.24
t-Statistic	1.60	-1.20	-2.40		1.10	6.35	-3.00	
p-Value	0.11	0.23	0.02		0.27	0.00	0.00	
RMW								
Coef.	0.30	-6.18	-16.97	12.48		-34.50	4.77	0.10
t-Statistic	2.27	-2.01	-1.56	1.23		-3.87	0.79	
p-Value	0.02	0.05	0.12	0.22		0.00	0.43	
CMA								
Coef.	0.36	-9.65	4.80	32.60	-17.51		6.75	0.26
t-Statistic	3.61	-4.97	1.15	7.58	-4.01		2.34	
p-Value	0.00	0.00	0.25	0.00	0.00		0.02	
UMD								
Coef.	0.93	-9.88	-16.67	-33.25	8.53	23.77		0.07
t-Statistic	4.50	-1.66	-1.56	-3.18	0.69	1.95		
p-Value	0.00	0.10	0.12	0.00	0.49	0.05		

Table C.13: Using five industry-specific factors to explain average returns on the sixth: June 1963 – June 2019, monthly returns, *Aggregate Factors*. All of the coefficients, except for R-squared, are expressed in percentage terms.

	Alpha (α)	R_{ind} - R_f	SMB	HML	RMW	CMA	UMD	R^2
R_{ind} - R_f								
Coef.	0.87		24.20	5.77	-33.40	-86.70	-12.80	0.25
t-Statistic	5.68		4.48	0.75	-4.39	-8.19	-3.46	
p-Value	0.00		0.00	0.45	0.00	0.00	0.00	
SMB								
Coef.	0.30	12.10		-7.23	-50.70	-11.00	3.39	0.22
t-Statistic	2.70	4.48		-1.34	-9.97	-1.40	1.29	
p-Value	0.01	0.00		0.18	0.00	0.16	0.20	
HML								
Coef.	0.09	1.48	-3.71		12.40	97.50	-12.10	0.52
t-Statistic	1.09	0.75	-1.34		3.20	23.50	-6.63	
p-Value	0.28	0.45	0.18		0.00	0.00	0.00	
RMW								
Coef.	0.36	-8.43	-25.60	12.20		-29.60	5.72	0.21
t-Statistic	4.65	-4.39	-9.97	3.20		-5.43	3.08	
p-Value	0.00	0.00	0.00	0.00		0.00	0.00	
CMA								
Coef.	0.20	-10.60	-2.68	46.40	-14.30		4.08	0.55
t-Statistic	3.73	-8.19	-1.40	23.50	-5.43		3.17	
p-Value	0.00	0.00	0.16	0.00	0.00		0.00	
UMD								
Coef.	0.71	-13.80	7.36	-51.20	24.50	36.30		0.10
t-Statistic	4.37	-3.46	1.29	-6.63	3.08	3.17		
p-Value	0.00	0.00	0.20	0.00	0.00	0.00		

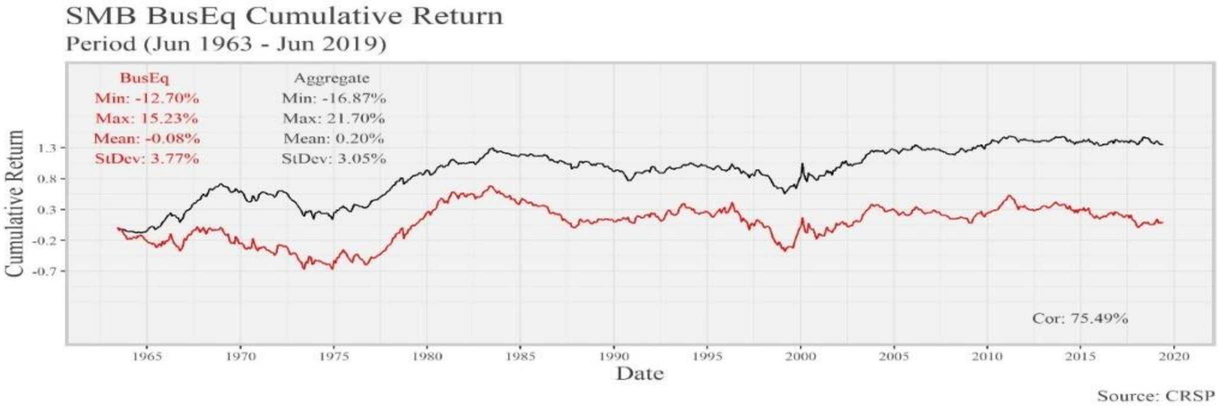
Appendix D: Regression results of high-performing industry factor portfolios

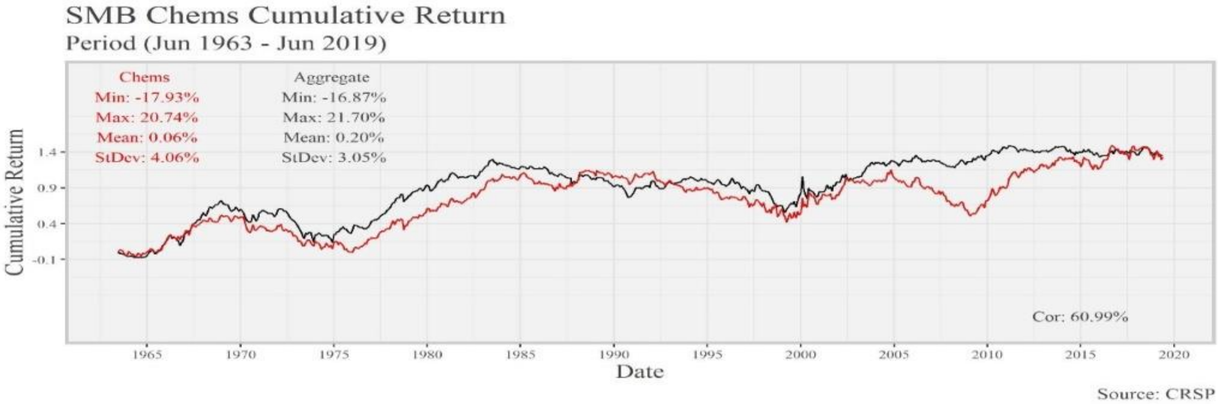
Table D.1: The Table presents the regression results of high-performing industries per each factor. The strategies are then regressed on the five aggregate factors (SMB, HML, RMW, CMA, UMD) and the historical excess market returns (R_m – R_f). The time period is June 1963 – June 2019, and the data includes monthly returns. The coefficients are expressed as percentages.

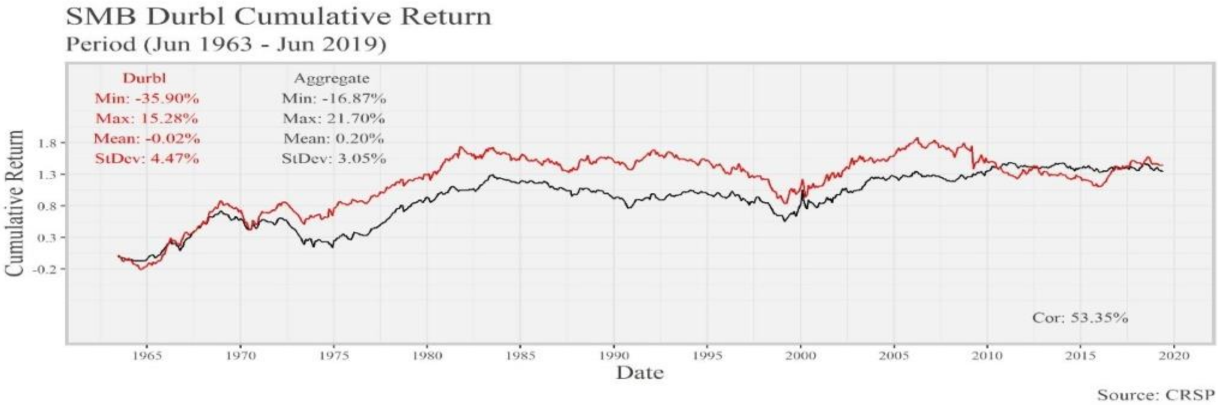
	Alpha (α)	Rm - Rf	SMB	HML	RMW	CMA	UMD
SMB (Short) NoDur							
Coef.	0.25	0.50	-81.10	-22.81	8.59	23.57	6.33
t-Statistic	2.67	0.16	-16.53	-3.79	0.98	2.56	2.16
p-Value	0.01	0.88	0.00	0.00	0.33	0.01	0.03
SMB Utils							
Coef.	0.11	-0.59	23.87	6.73	4.19	-0.27	0.57
t-Statistic	1.70	-0.34	7.75	1.72	1.24	-0.04	0.24
p-Value	0.09	0.73	0.00	0.09	0.22	0.97	0.81
HML Energy							
Coef.	0.43	4.80	7.26	48.39	-10.61	-4.05	0.00
t-Statistic	2.50	1.03	1.06	4.94	-1.08	-0.33	0.00
p-Value	0.01	0.30	0.29	0.00	0.28	0.74	1.00
HML NoDur							
Coef.	0.10	13.37	17.03	55.17	-3.28	-3.80	0.61
t-Statistic	0.97	4.18	3.62	9.52	-0.48	-0.58	0.18
p-Value	0.33	0.00	0.00	0.00	0.63	0.56	0.86
HML Utils							
Coef.	0.31	-11.49	3.99	25.92	-6.75	-10.31	0.16
t-Statistic	3.04	-3.43	0.98	4.04	-1.08	-1.13	0.04
p-Value	0.00	0.00	0.33	0.00	0.28	0.26	0.97
CMA Hlth							
Coef.	0.31	2.20	-1.55	6.64	-3.89	40.98	-1.21
t-Statistic	2.54	0.72	-0.35	0.91	-0.59	3.95	-0.32
p-Value	0.01	0.47	0.73	0.36	0.56	0.00	0.75
CMA Other							
Coef.	0.25	-2.37	-2.95	-2.31	-10.69	71.21	6.18
t-Statistic	2.29	-0.89	-0.59	-0.47	-1.57	8.28	2.19
p-Value	0.02	0.37	0.56	0.64	0.12	0.00	0.03
CMA Utils							
Coef.	0.16	-3.34	-1.05	-0.29	15.18	12.85	-2.41
t-Statistic	1.90	-1.44	-0.43	-0.07	3.60	2.08	-0.90
p-Value	0.06	0.15	0.67	0.94	0.00	0.04	0.37
UMD BusEq							
Coef.	0.36	1.57	-8.42	-1.29	-5.27	-13.02	87.77
t-Statistic	2.31	0.33	-1.14	-0.14	-0.43	-0.89	11.83
p-Value	0.02	0.74	0.26	0.89	0.67	0.38	0.00
UMD Other							
Coef.	0.29	-0.13	-7.74	0.11	8.03	-0.14	90.89
t-Statistic	2.31	-0.03	-1.27	0.02	0.76	-0.01	20.66
p-Value	0.02	0.97	0.20	0.99	0.45	0.99	0.00

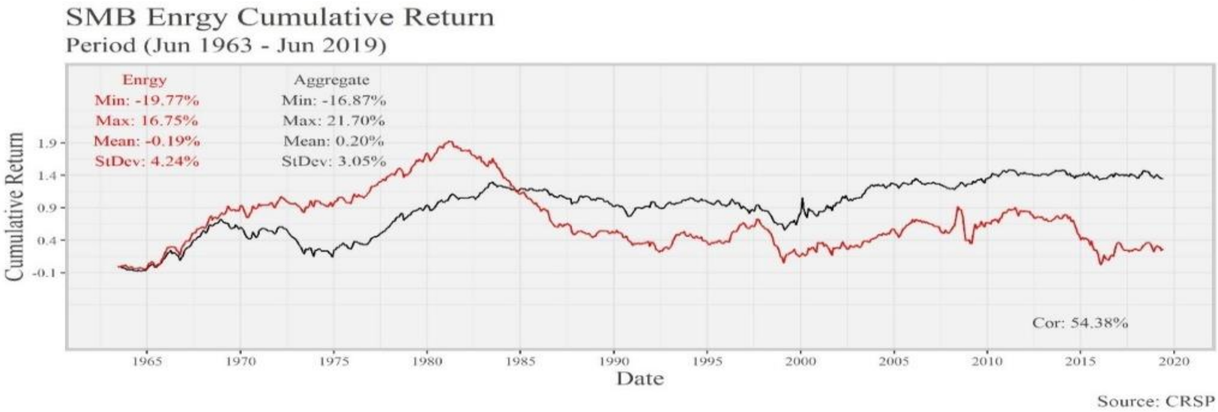
Appendix E: Comparison charts Industry vs Aggregate returns

Figure E.1: *The following 12 charts represent the cumulative returns of SMB and its respective industries, together with the following summary statistics: Min, Max, Mean, Standard Deviation, Correlation*

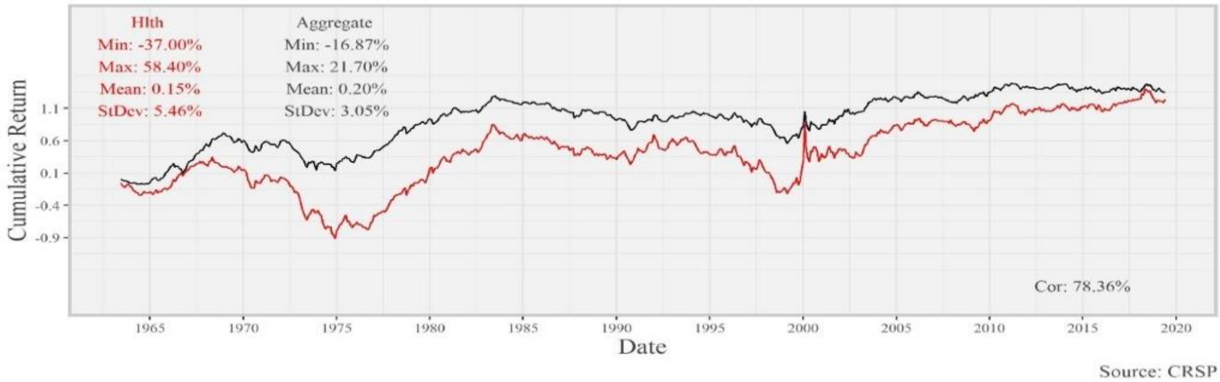




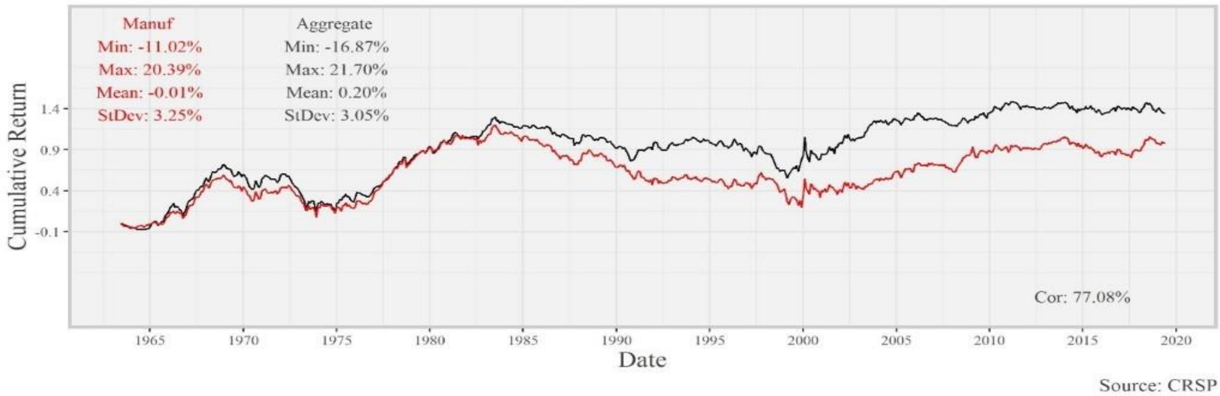




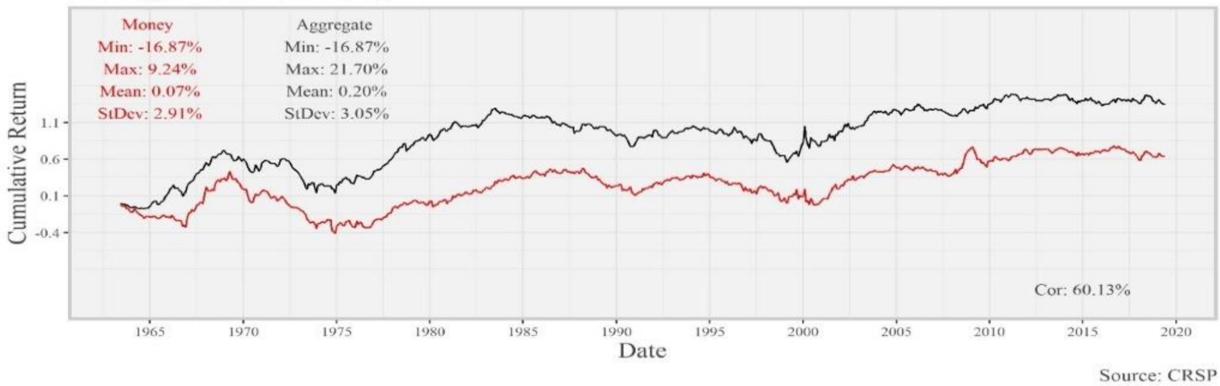
SMB Hlth Cumulative Return
Period (Jun 1963 - Jun 2019)



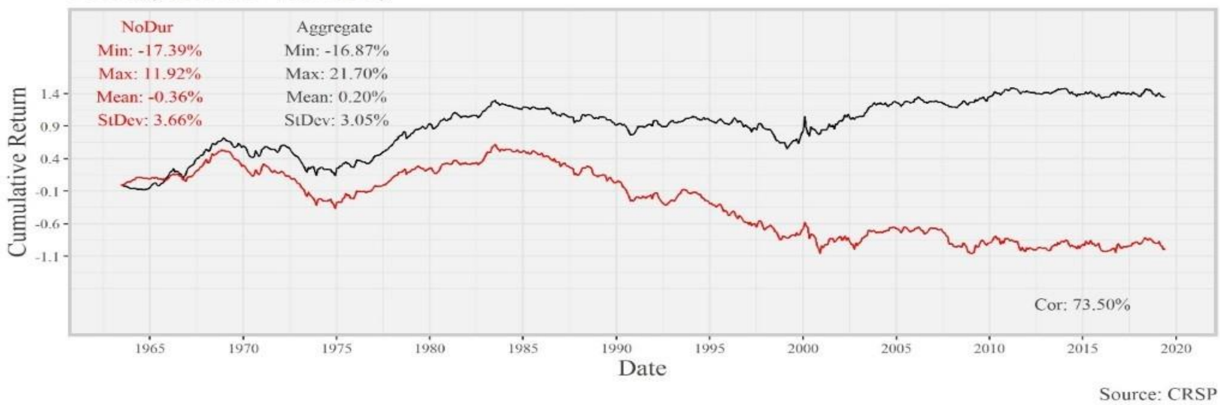
SMB Manuf Cumulative Return
Period (Jun 1963 - Jun 2019)



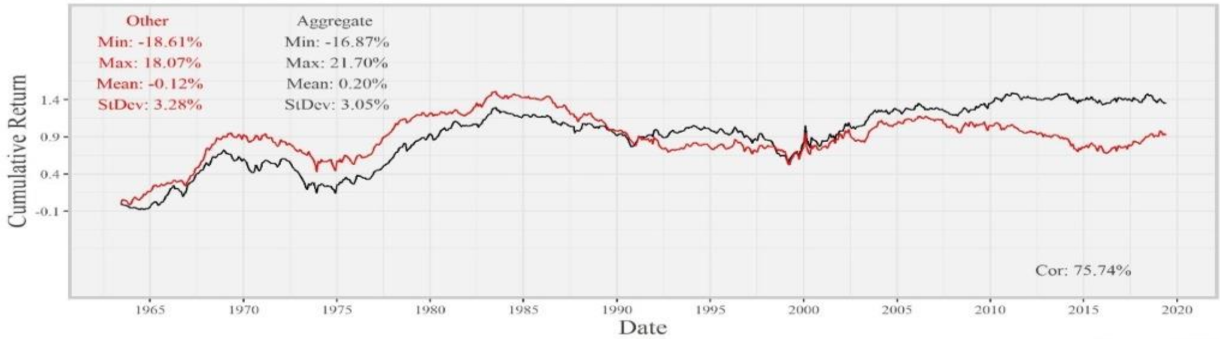
SMB Money Cumulative Return
Period (Jun 1963 - Jun 2019)



SMB NoDur Cumulative Return
Period (Jun 1963 - Jun 2019)

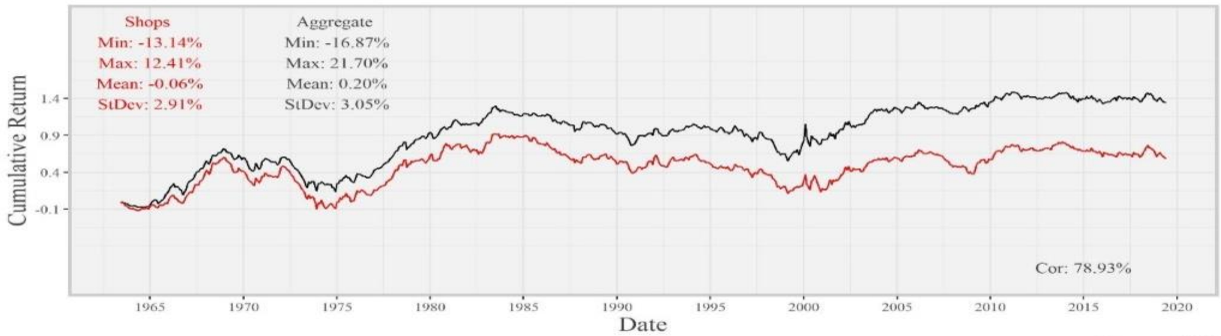


SMB Other Cumulative Return
Period (Jun 1963 - Jun 2019)



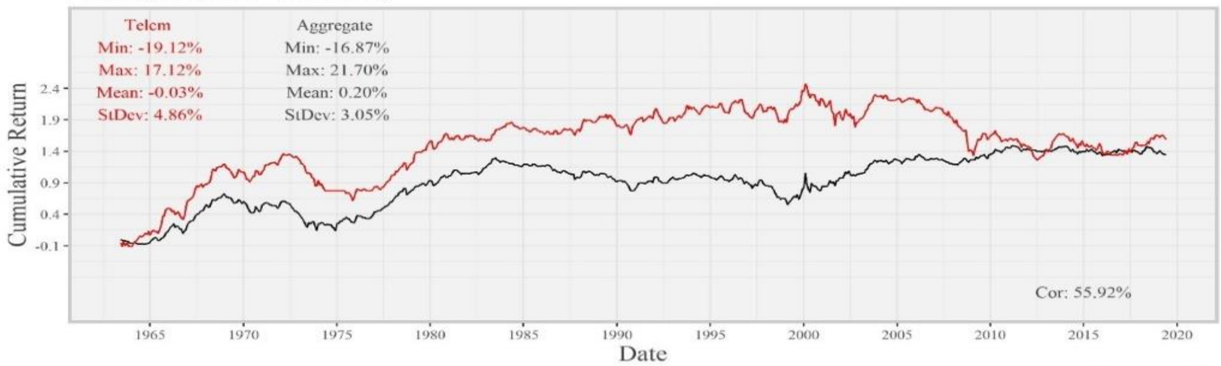
Source: CRSP

SMB Shops Cumulative Return
Period (Jun 1963 - Jun 2019)



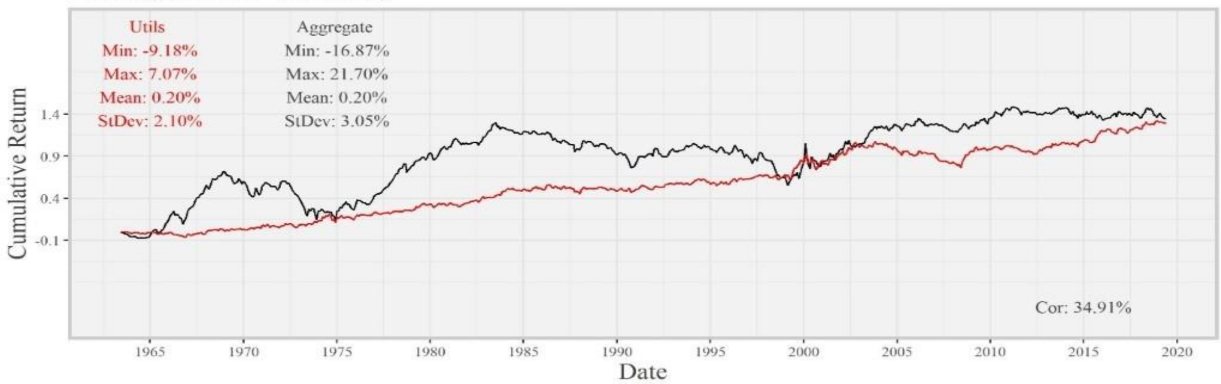
Source: CRSP

SMB Telcm Cumulative Return
Period (Jun 1963 - Jun 2019)



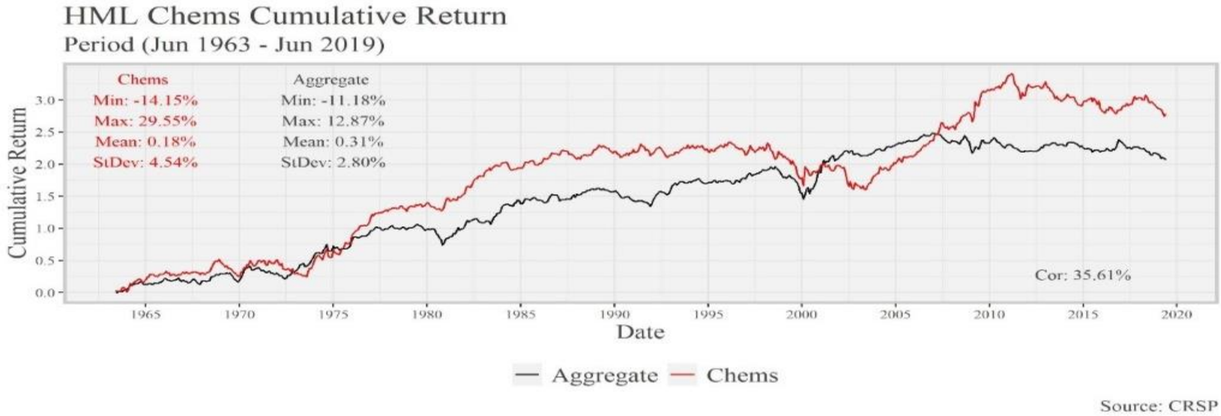
Source: CRSP

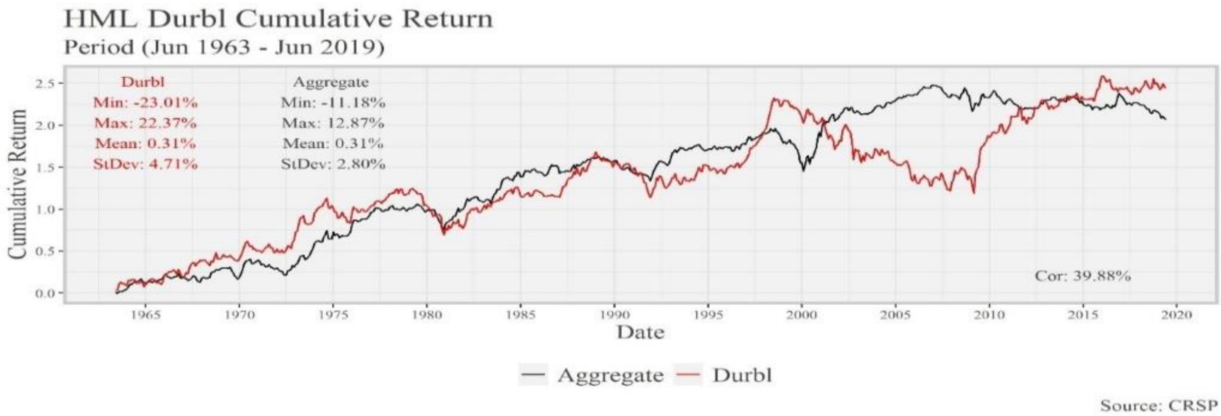
SMB Utils Cumulative Return
Period (Jun 1963 - Jun 2019)

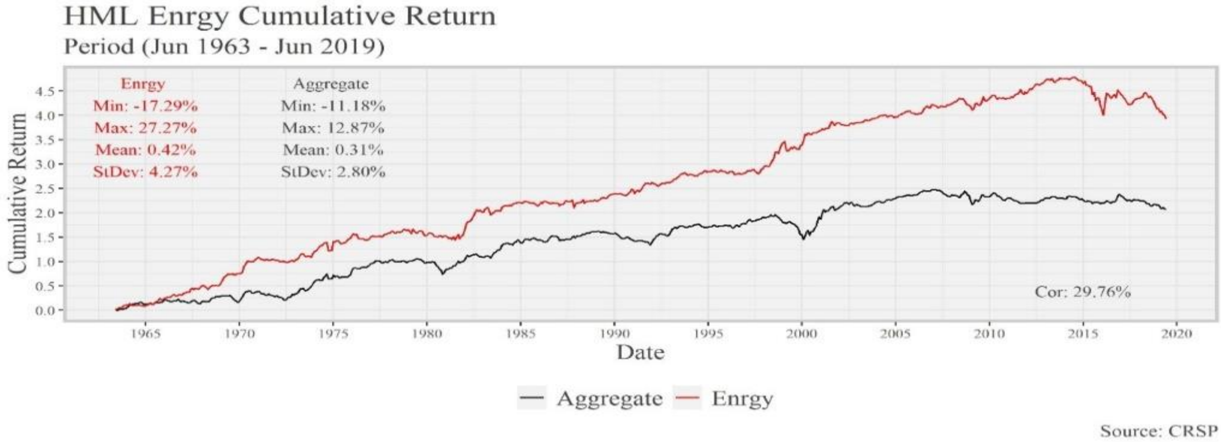


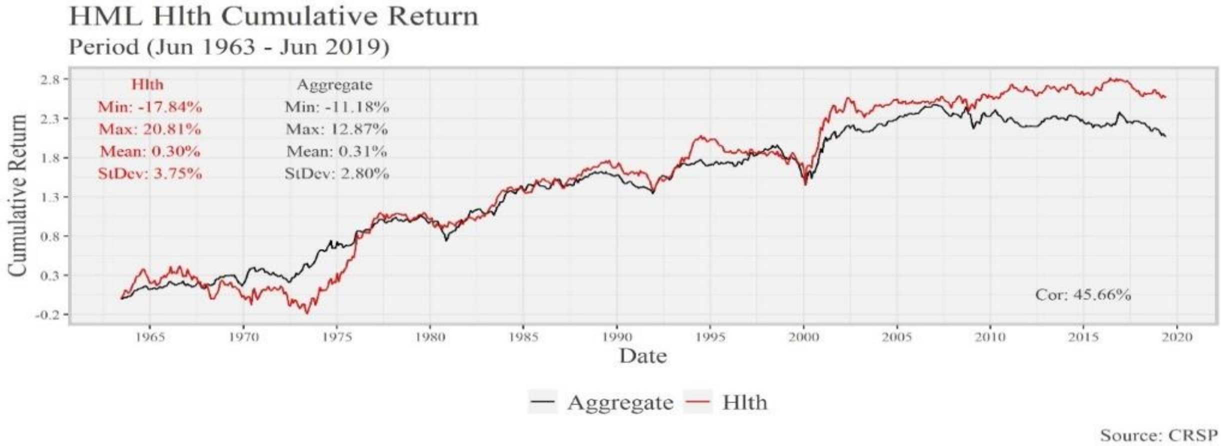
Source: CRSP

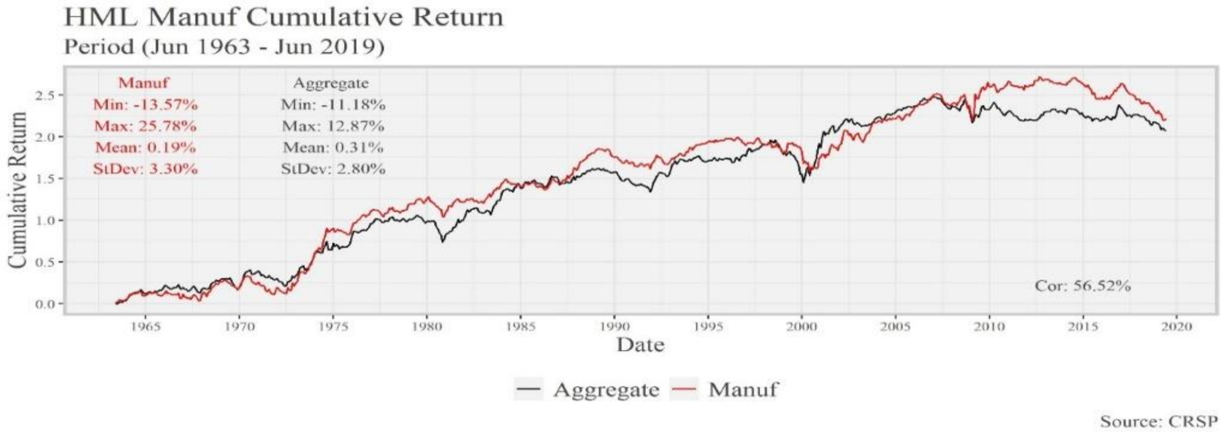
Figure E.2: *The following 12 charts represent the cumulative returns of HML and its respective industries, together with the following summary statistics: Min, Max, Mean, Standard Deviation, Correlation*

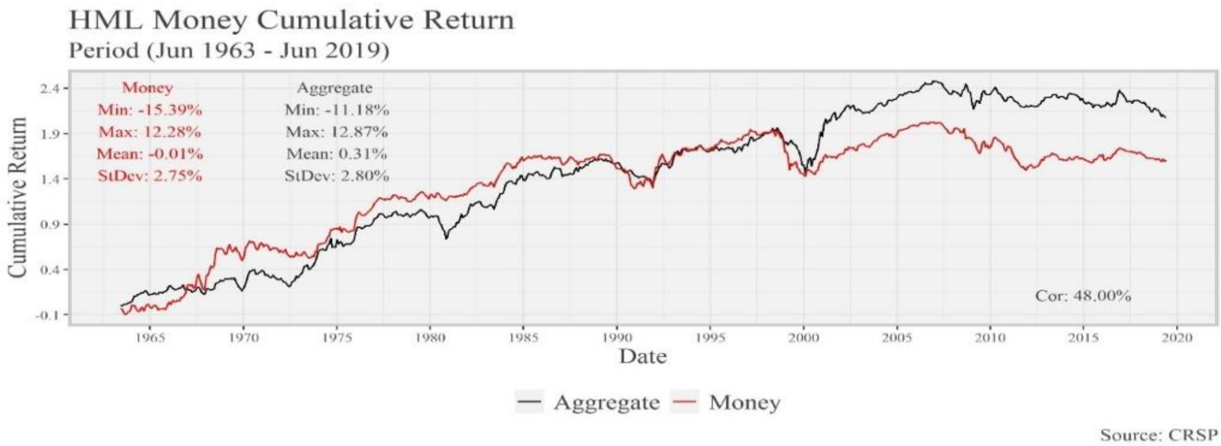


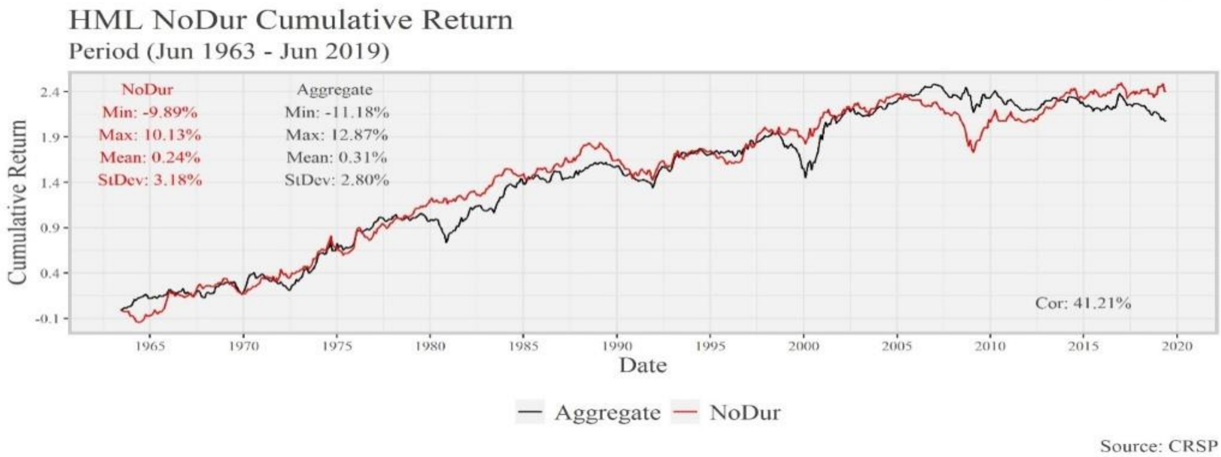


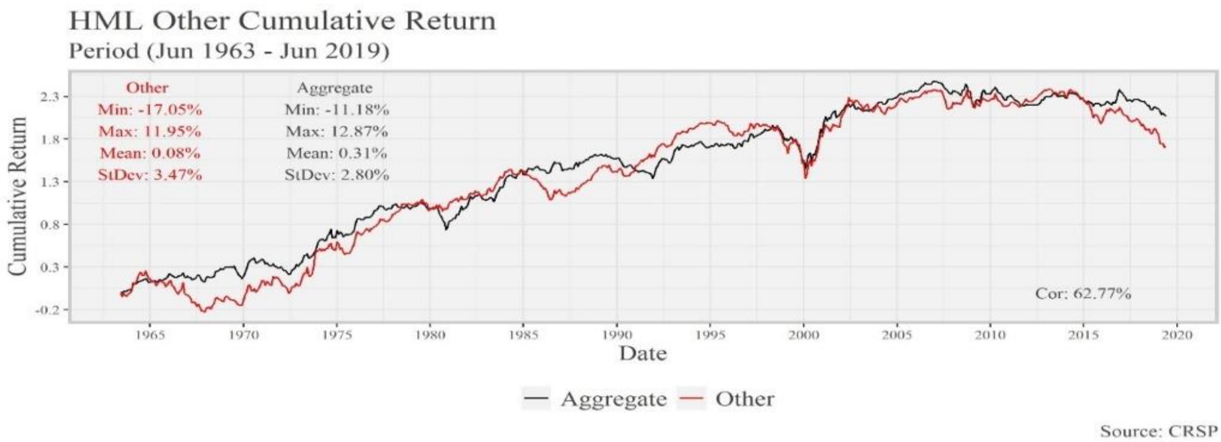


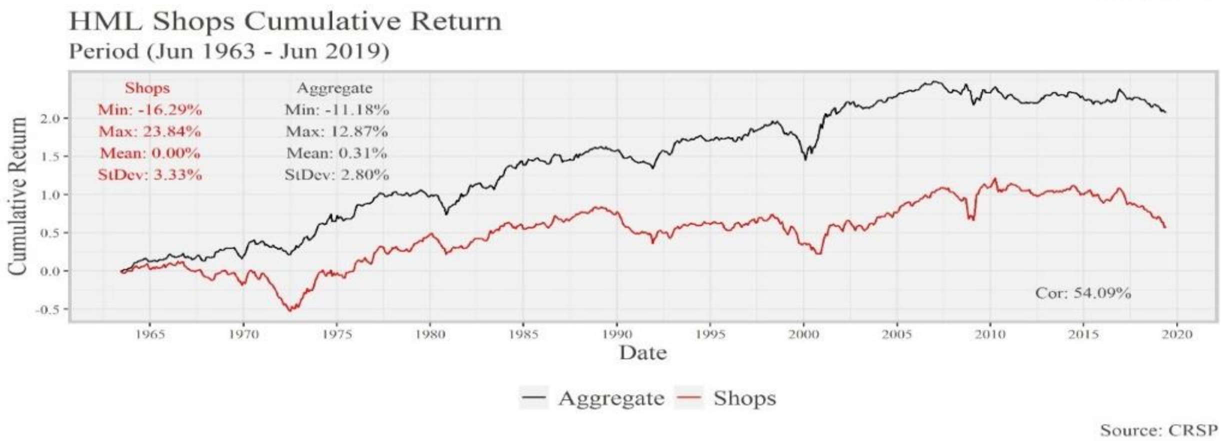

HML Hlth Cumulative Return
Period (Jun 1963 - Jun 2019)
Hlth
Min: -17.84%
Max: 20.81%
Mean: 0.30%
StDev: 3.75%
Aggregate
Min: -11.18%
Max: 12.87%
Mean: 0.31%
StDev: 2.80%
Cor: 45.66%
Cumulative Return
Date
Aggregate
Hlth
Source: CRSP

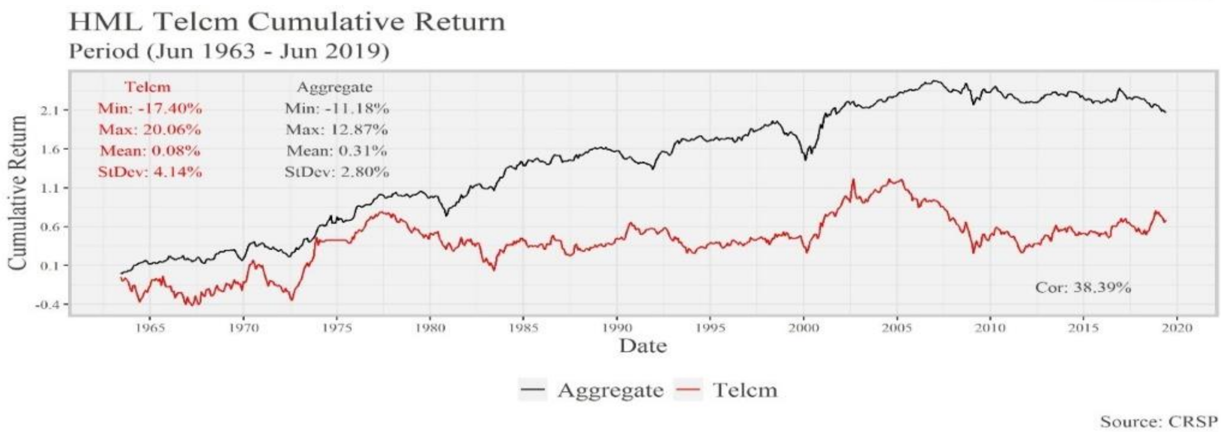

HML Manuf Cumulative Return
Period (Jun 1963 - Jun 2019)
Manuf
Min: -13.57%
Max: 25.78%
Mean: 0.19%
StDev: 3.30%
Aggregate
Min: -11.18%
Max: 12.87%
Mean: 0.31%
StDev: 2.80%
Cor: 56.52%
Cumulative Return
Date
Aggregate
Manuf
Source: CRSP


HML Money Cumulative Return
Period (Jun 1963 - Jun 2019)
Money
Min: -15.39%
Max: 12.28%
Mean: -0.01%
StDev: 2.75%
Aggregate
Min: -11.18%
Max: 12.87%
Mean: 0.31%
StDev: 2.80%
Cor: 48.00%
Cumulative Return
Date
Aggregate
Money
Source: CRSP


HML NoDur Cumulative Return
Period (Jun 1963 - Jun 2019)
NoDur
Min: -9.89%
Max: 10.13%
Mean: 0.24%
StDev: 3.18%
Aggregate
Min: -11.18%
Max: 12.87%
Mean: 0.31%
StDev: 2.80%
Cor: 41.21%
Cumulative Return
Date
Aggregate
NoDur
Source: CRSP

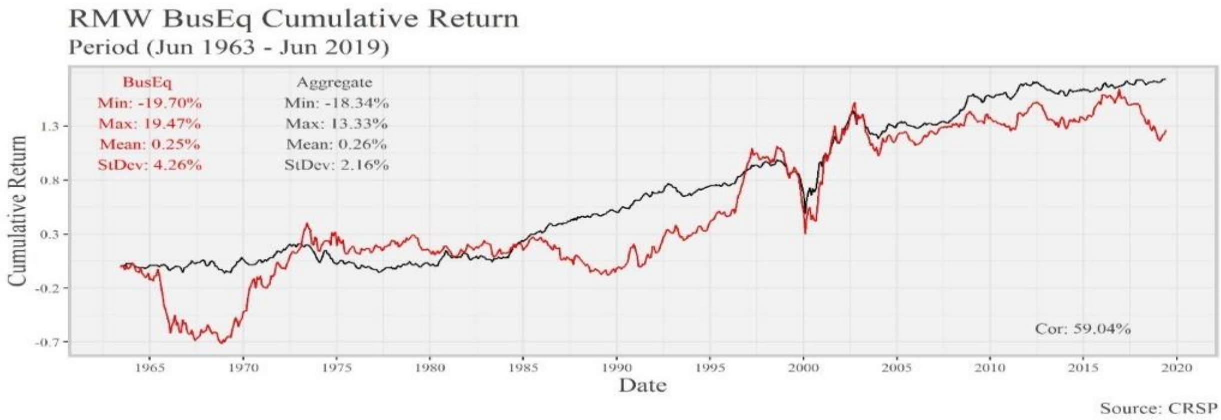

HML Other Cumulative Return
Period (Jun 1963 - Jun 2019)
Other
Min: -17.05%
Max: 11.95%
Mean: 0.08%
StDev: 3.47%
Aggregate
Min: -11.18%
Max: 12.87%
Mean: 0.31%
StDev: 2.80%
Cor: 62.77%
Cumulative Return
Date
Aggregate
Other
Source: CRSP

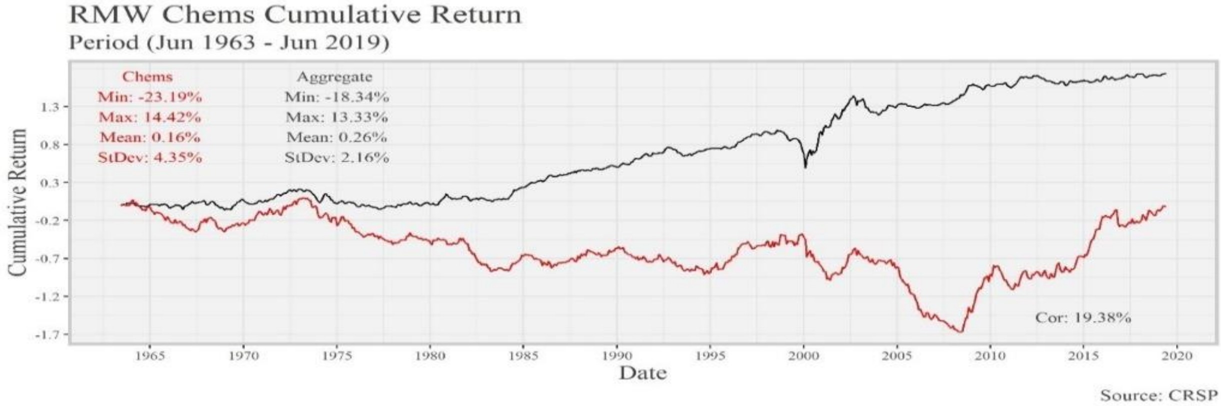

HML Shops Cumulative Return
Period (Jun 1963 - Jun 2019)
Shops
Min: -16.29%
Max: 23.84%
Mean: 0.00%
StDev: 3.33%
Aggregate
Min: -11.18%
Max: 12.87%
Mean: 0.31%
StDev: 2.80%
Cor: 54.09%
Cumulative Return
Date
Aggregate
Shops
Source: CRSP

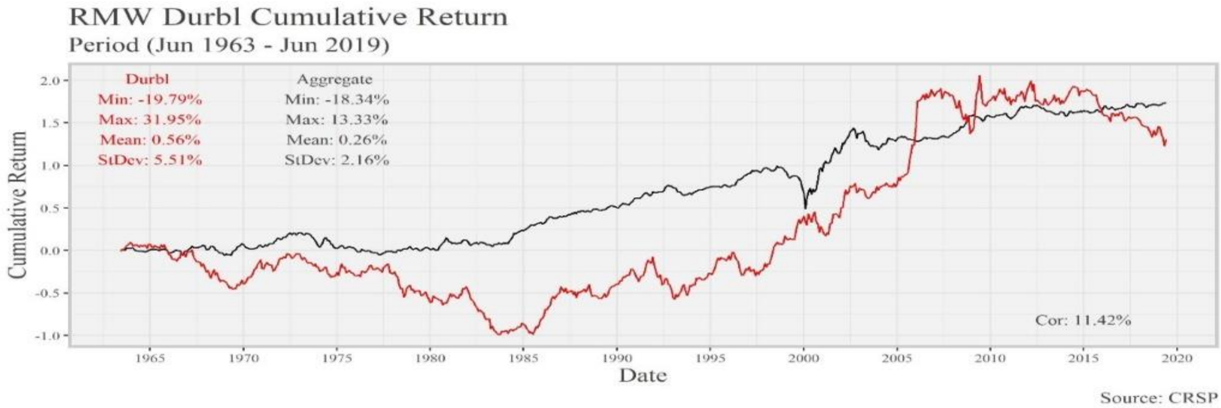

HML Telcm Cumulative Return
Period (Jun 1963 - Jun 2019)
Telcm
Min: -17.40%
Max: 20.06%
Mean: 0.08%
StDev: 4.14%
Aggregate
Min: -11.18%
Max: 12.87%
Mean: 0.31%
StDev: 2.80%
Cor: 38.39%
Cumulative Return
Date
Aggregate
Telcm
Source: CRSP

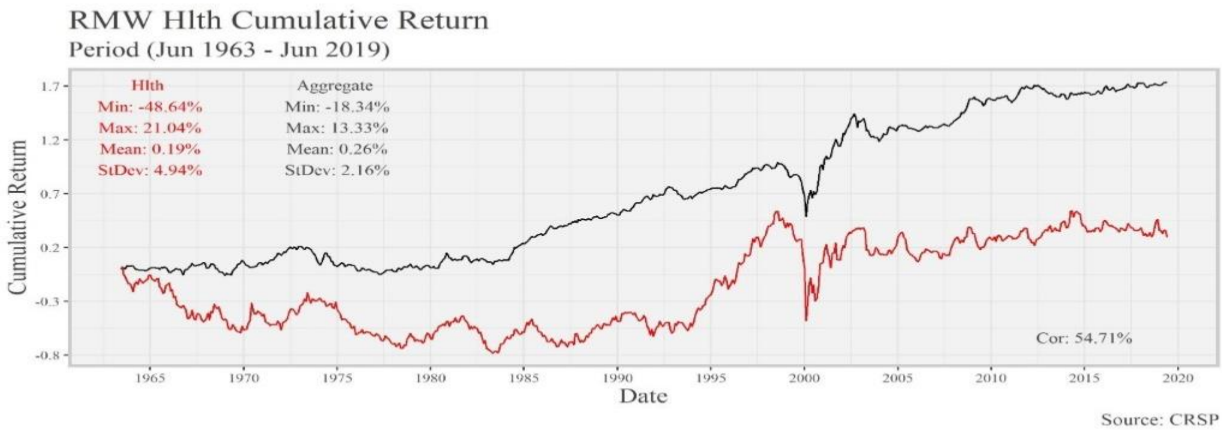

HML Utils Cumulative Return
Period (Jun 1963 - Jun 2019)
Utils
Min: -7.66%
Max: 12.67%
Mean: 0.32%
StDev: 2.35%
Aggregate
Min: -11.18%
Max: 12.87%
Mean: 0.31%
StDev: 2.80%
Cor: 27.74%
Cumulative Return
Date
Aggregate
Utils
Source: CRSP

Figure E.3: *The following 12 charts represent the cumulative returns of RMW and its respective industries, together with the following summary statistics: Min, Max, Mean, Standard Deviation, Correlation*

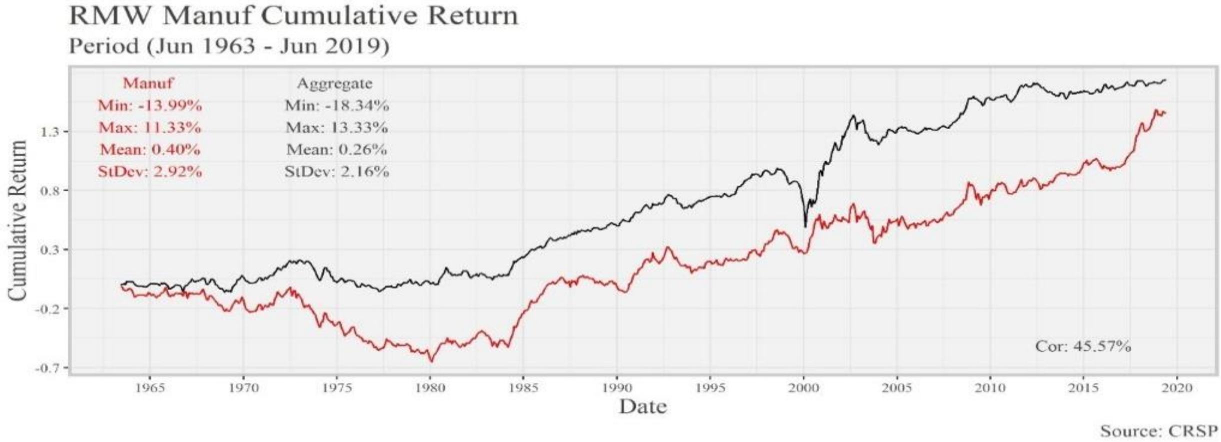






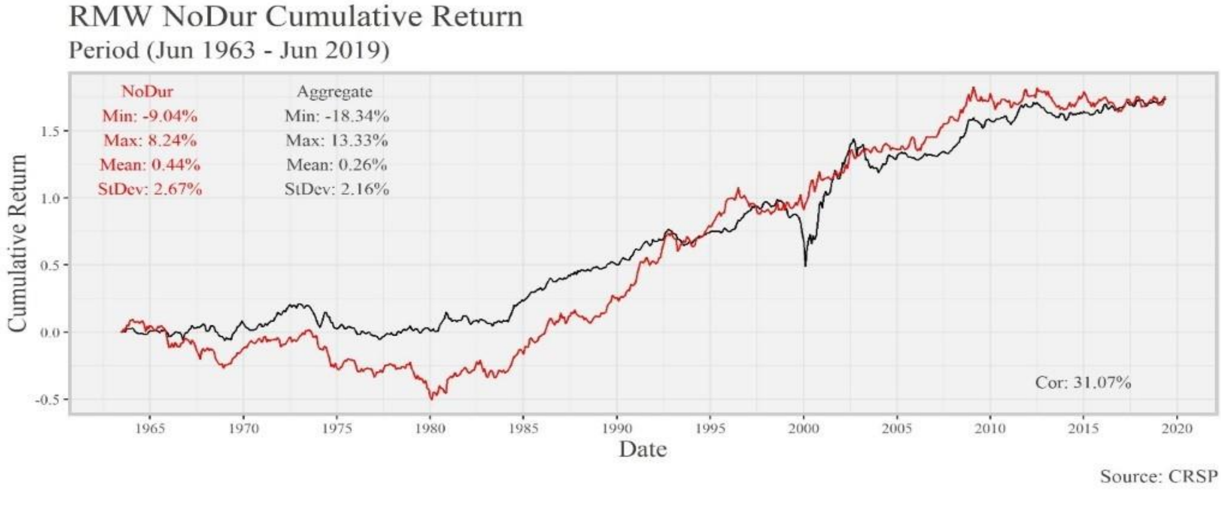


RMW Hlth Cumulative Return
Period (Jun 1963 - Jun 2019)
Hlth
Min: -48.64%
Max: 21.04%
Mean: 0.19%
StDev: 4.94%
Aggregate
Min: -18.34%
Max: 13.33%
Mean: 0.26%
StDev: 2.16%
Cor: 54.71%
Cumulative Return
Date
Source: CRSP

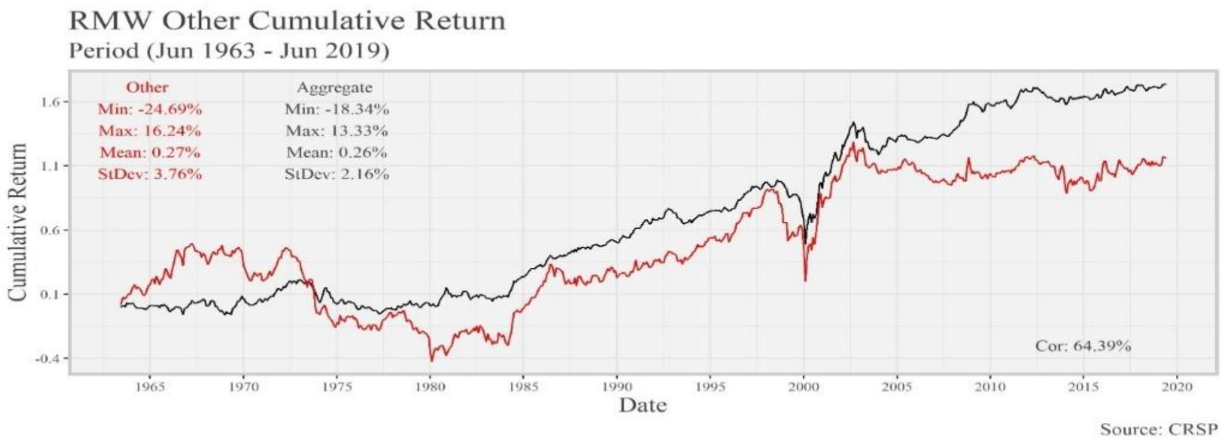


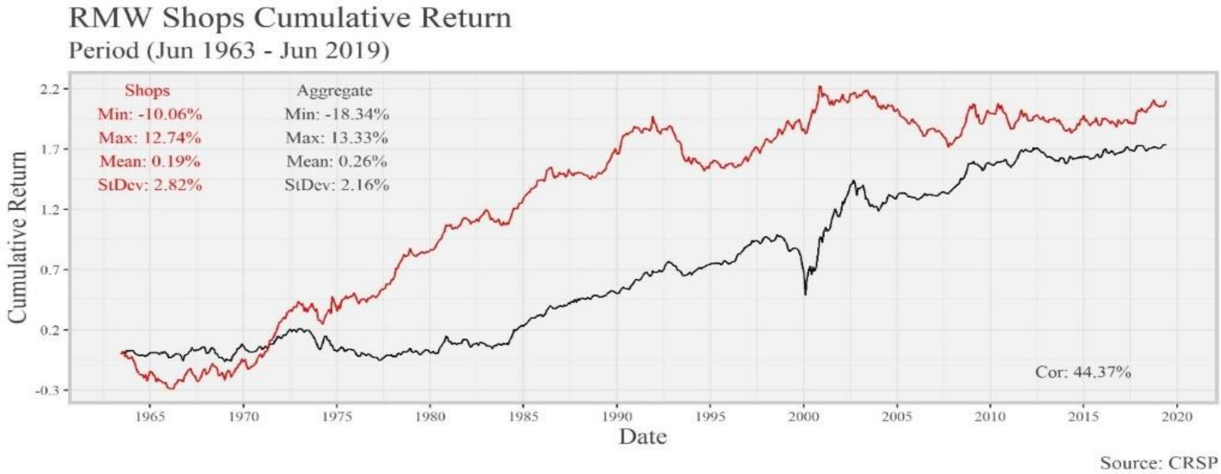
RMW Manuf Cumulative Return
Period (Jun 1963 - Jun 2019)
Manuf
Min: -13.99%
Max: 11.33%
Mean: 0.40%
StDev: 2.92%
Aggregate
Min: -18.34%
Max: 13.33%
Mean: 0.26%
StDev: 2.16%
Cor: 45.57%
Cumulative Return
Date
Source: CRSP

RMW Money Cumulative Return
Period (Jun 1963 - Jun 2019)
Money
Min: -10.43%
Max: 14.34%
Mean: 0.32%
StDev: 2.38%
Aggregate
Min: -18.34%
Max: 13.33%
Mean: 0.26%
StDev: 2.16%
Cor: 20.00%
Cumulative Return
Date
Source: CRSP



RMW NoDur Cumulative Return
Period (Jun 1963 - Jun 2019)
NoDur
Min: -9.04%
Max: 8.24%
Mean: 0.44%
StDev: 2.67%
Aggregate
Min: -18.34%
Max: 13.33%
Mean: 0.26%
StDev: 2.16%
Cor: 31.07%
Cumulative Return
Date
Source: CRSP


RMW Other Cumulative Return
Period (Jun 1963 - Jun 2019)
Other
Min: -24.69%
Max: 16.24%
Mean: 0.27%
StDev: 3.76%
Aggregate
Min: -18.34%
Max: 13.33%
Mean: 0.26%
StDev: 2.16%
Cor: 64.39%
Cumulative Return
Date
Source: CRSP


RMW Shops Cumulative Return
Period (Jun 1963 - Jun 2019)
Shops
Min: -10.06%
Max: 12.74%
Mean: 0.19%
StDev: 2.82%
Aggregate
Min: -18.34%
Max: 13.33%
Mean: 0.26%
StDev: 2.16%
Cor: 44.37%
Cumulative Return
Date
Source: CRSP


RMW Telcm Cumulative Return
Period (Jun 1963 - Jun 2019)
Telcm
Min: -18.20%
Max: 29.16%
Mean: 0.52%
StDev: 5.12%
Aggregate
Min: -18.34%
Max: 13.33%
Mean: 0.26%
StDev: 2.16%
Cor: 38.96%
Cumulative Return
Date
Source: CRSP

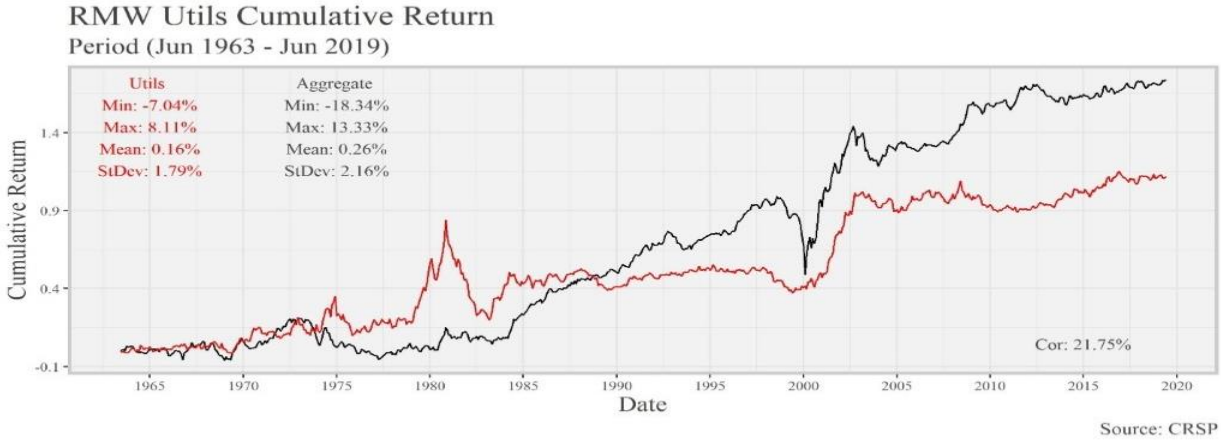
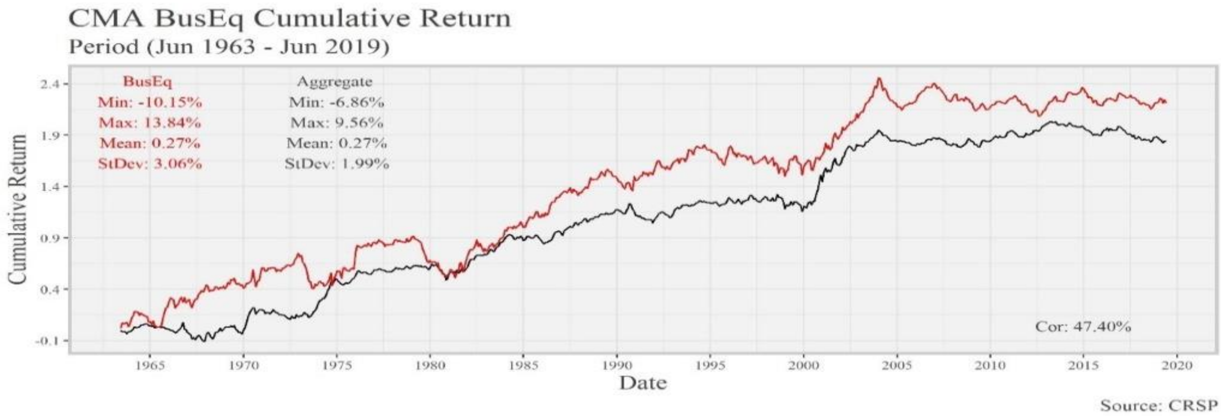
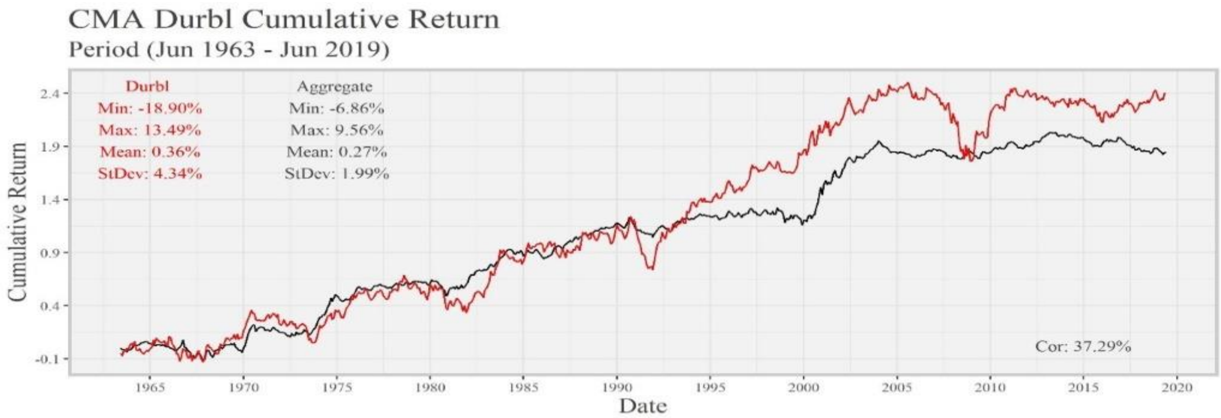
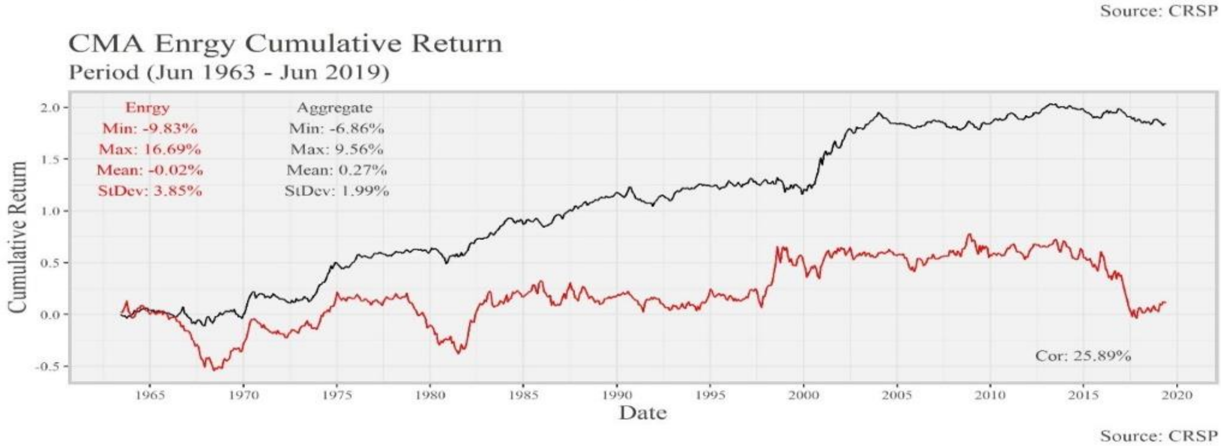

RMW Utils Cumulative Return
Period (Jun 1963 - Jun 2019)
Utils
Min: -7.04%
Max: 8.11%
Mean: 0.16%
StDev: 1.79%
Aggregate
Min: -18.34%
Max: 13.33%
Mean: 0.26%
StDev: 2.16%
Cor: 21.75%
Cumulative Return
Date
Source: CRSP

Figure E.4: *The following 12 charts represent the cumulative returns of CMA and its respective industries, together with the following summary statistics: Min, Max, Mean, Standard Deviation, Correlation*

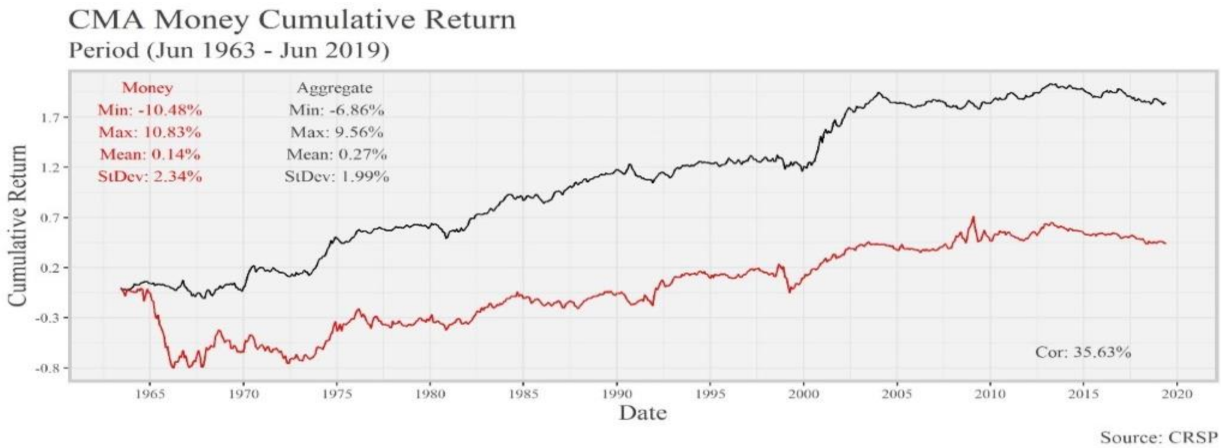







CMA Hlth Cumulative Return
Period (Jun 1963 - Jun 2019)
Hlth
Min: -8.02%
Max: 12.87%
Mean: 0.44%
StDev: 2.76%
Aggregate
Min: -6.86%
Max: 9.56%
Mean: 0.27%
StDev: 1.99%
Cor: 30.68%
Cumulative Return
Date
Source: CRSP

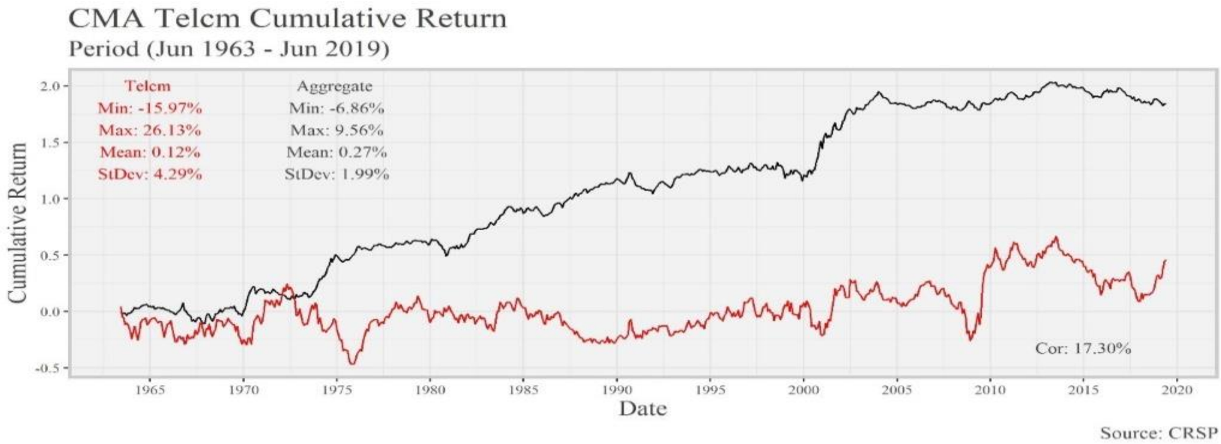

CMA Manuf Cumulative Return
Period (Jun 1963 - Jun 2019)
Manuf
Min: -6.92%
Max: 10.15%
Mean: 0.22%
StDev: 2.67%
Aggregate
Min: -6.86%
Max: 9.56%
Mean: 0.27%
StDev: 1.99%
Cor: 56.56%
Cumulative Return
Date
Source: CRSP


CMA Money Cumulative Return
Period (Jun 1963 - Jun 2019)
Money
Min: -10.48%
Max: 10.83%
Mean: 0.14%
StDev: 2.34%
Aggregate
Min: -6.86%
Max: 9.56%
Mean: 0.27%
StDev: 1.99%
Cor: 35.63%
Cumulative Return
Date
Source: CRSP


CMA NoDur Cumulative Return
Period (Jun 1963 - Jun 2019)
NoDur
Min: -9.81%
Max: 8.28%
Mean: 0.13%
StDev: 2.47%
Aggregate
Min: -6.86%
Max: 9.56%
Mean: 0.27%
StDev: 1.99%
Cor: 31.04%
Cumulative Return
Date
Source: CRSP

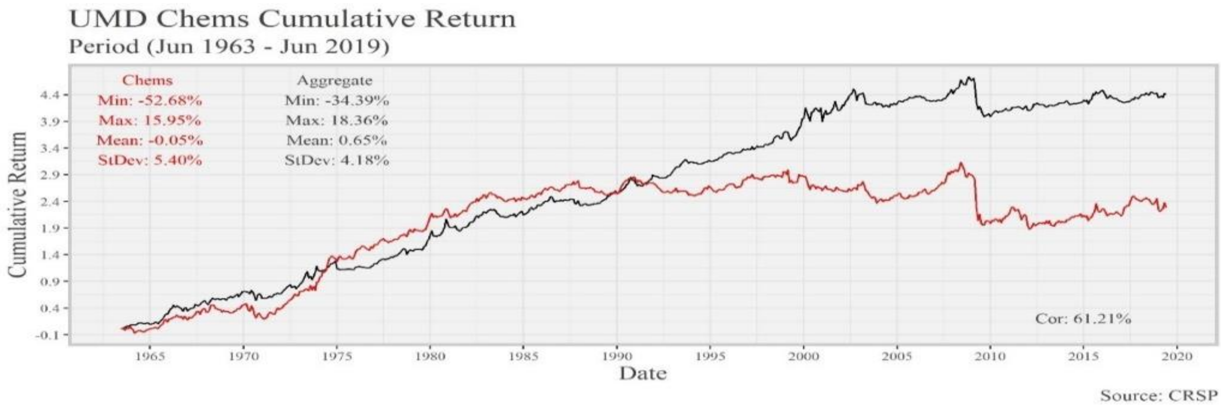

CMA Other Cumulative Return
Period (Jun 1963 - Jun 2019)
Other
Min: -6.74%
Max: 11.53%
Mean: 0.34%
StDev: 2.71%
Aggregate
Min: -6.86%
Max: 9.56%
Mean: 0.27%
StDev: 1.99%
Cor: 51.15%
Cumulative Return
Date
Source: CRSP


CMA Shops Cumulative Return
Period (Jun 1963 - Jun 2019)
Shops
Min: -10.54%
Max: 7.67%
Mean: 0.14%
StDev: 2.51%
Aggregate
Min: -6.86%
Max: 9.56%
Mean: 0.27%
StDev: 1.99%
Cor: 48.89%
Cumulative Return
Date
Source: CRSP


CMA Telcm Cumulative Return
Period (Jun 1963 - Jun 2019)
Telcm
Min: -15.97%
Max: 26.13%
Mean: 0.12%
StDev: 4.29%
Aggregate
Min: -6.86%
Max: 9.56%
Mean: 0.27%
StDev: 1.99%
Cor: 17.30%
Cumulative Return
Date
Source: CRSP

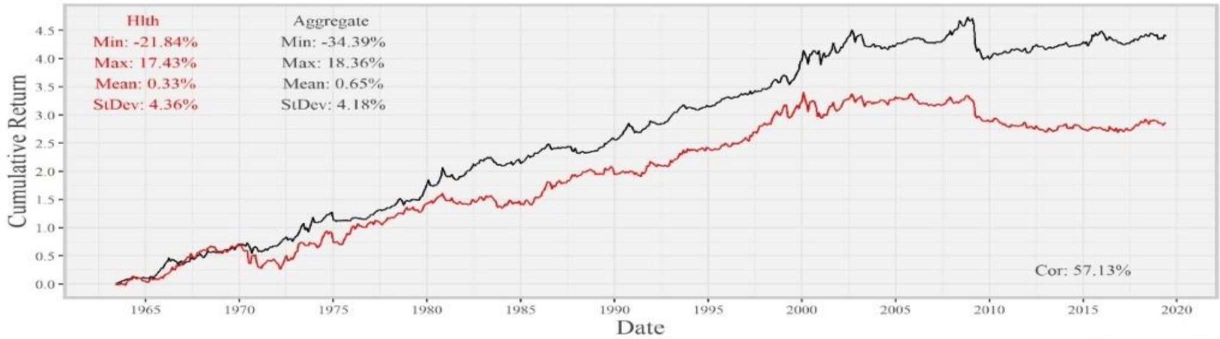

CMA Utils Cumulative Return
Period (Jun 1963 - Jun 2019)
Utils
Min: -6.61%
Max: 9.20%
Mean: 0.23%
StDev: 1.94%
Aggregate
Min: -6.86%
Max: 9.56%
Mean: 0.27%
StDev: 1.99%
Cor: 16.75%
Cumulative Return
Date
Source: CRSP

Figure E.5: *The following 12 charts represent the cumulative returns of UMD and its respective industries, together with the following summary statistics: Min, Max, Mean, Standard Deviation, Correlation*



UMD Hlth Cumulative Return

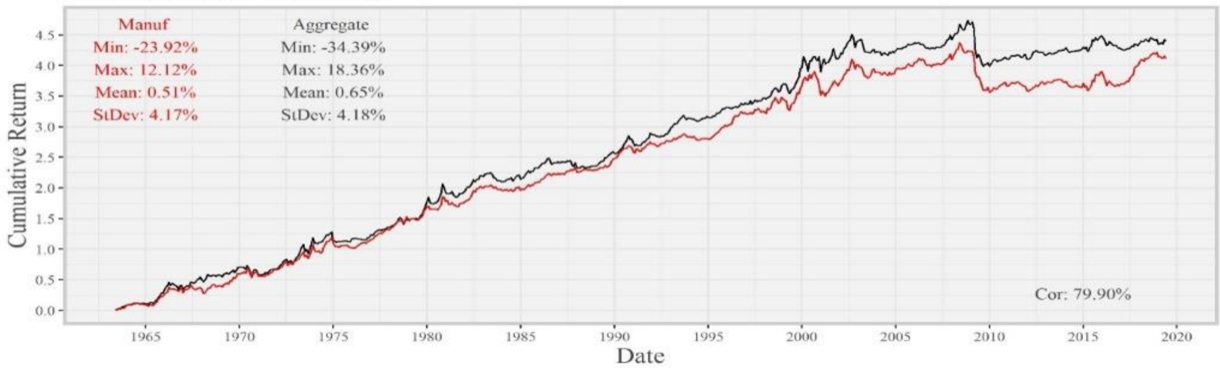
Period (Jun 1963 - Jun 2019)



Source: CRSP

UMD Manuf Cumulative Return

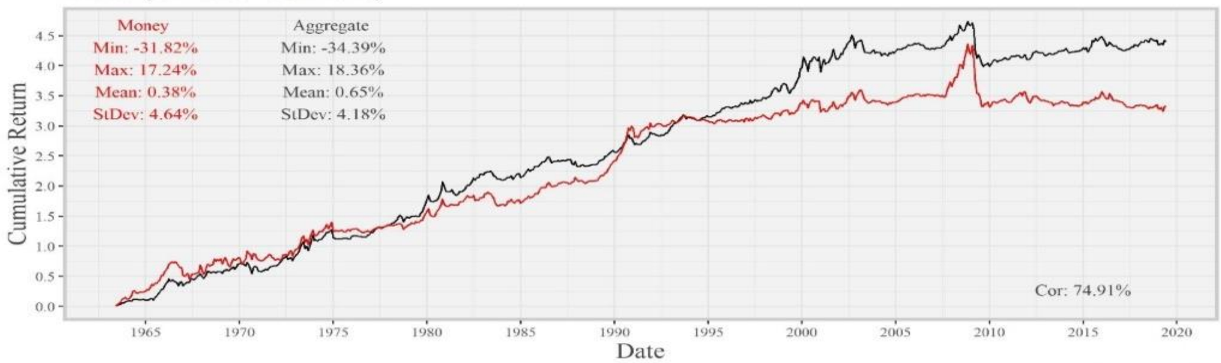
Period (Jun 1963 - Jun 2019)



Source: CRSP

UMD Money Cumulative Return

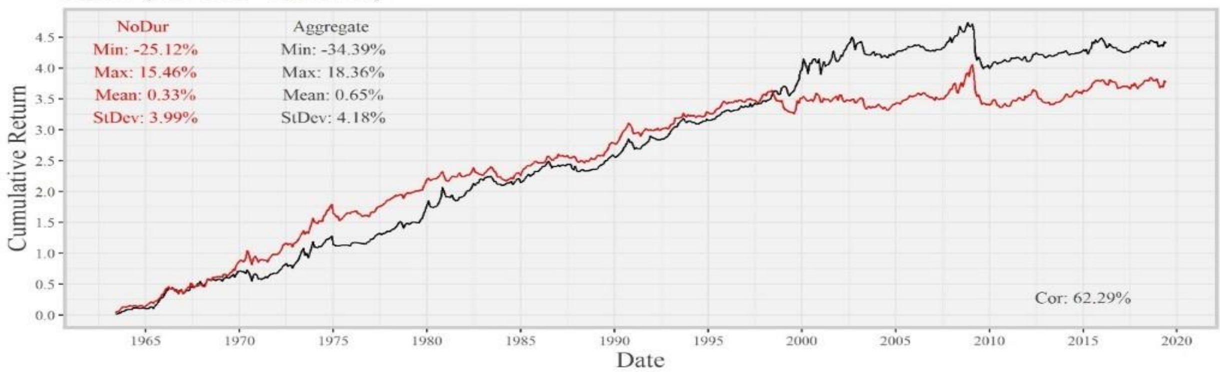
Period (Jun 1963 - Jun 2019)



Source: CRSP

UMD NoDur Cumulative Return

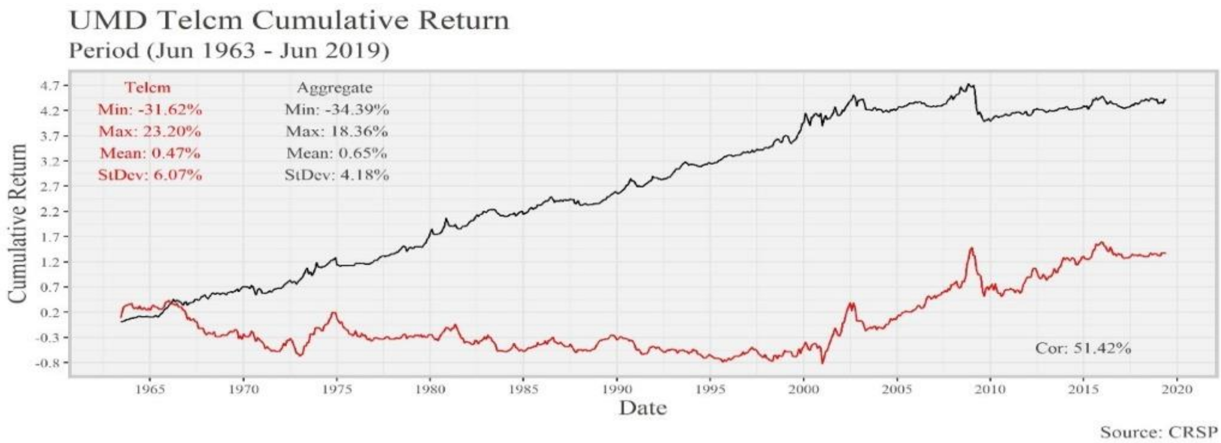
Period (Jun 1963 - Jun 2019)



Source: CRSP


UMD Other Cumulative Return
Period (Jun 1963 - Jun 2019)
Other
Min: -35.76%
Max: 14.03%
Mean: 0.64%
StDev: 4.76%
Aggregate
Min: -34.39%
Max: 18.36%
Mean: 0.65%
StDev: 4.18%
Cor: 81.16%
Cumulative Return
Date
Source: CRSP


UMD Shops Cumulative Return
Period (Jun 1963 - Jun 2019)
Shops
Min: -42.76%
Max: 15.53%
Mean: 0.38%
StDev: 4.54%
Aggregate
Min: -34.39%
Max: 18.36%
Mean: 0.65%
StDev: 4.18%
Cor: 75.16%
Cumulative Return
Date
Source: CRSP


UMD Telcm Cumulative Return
Period (Jun 1963 - Jun 2019)
Telcm
Min: -31.62%
Max: 23.20%
Mean: 0.47%
StDev: 6.07%
Aggregate
Min: -34.39%
Max: 18.36%
Mean: 0.65%
StDev: 4.18%
Cor: 51.42%
Cumulative Return
Date
Source: CRSP


UMD Utils Cumulative Return
Period (Jun 1963 - Jun 2019)
Utils
Min: -26.15%
Max: 21.67%
Mean: 0.15%
StDev: 3.70%
Aggregate
Min: -34.39%
Max: 18.36%
Mean: 0.65%
StDev: 4.18%
Cor: 54.63%
Cumulative Return
Date
Source: CRSP

Appendix F.1: Average monthly excess returns (%) for industry portfolios formed on Size (SMB) and Value (HML), 1926-2019.

1. NoDur

	Low	2	3	4	High	Avg.
Small	-0.22	0.91	0.53	0.90	1.31	**0.69**
2	0.64	0.43	0.94	0.78	1.15	**0.79**
3	0.59	0.81	0.92	0.81	1.01	**0.83**
4	0.80	0.66	0.89	0.65	1.01	**0.80**
Big	0.64	0.83	0.65	1.00	0.40	**0.70**
Avg.	**0.49**	**0.73**	**0.78**	**0.83**	**0.98**	
Avg HML						**0.49**
Avg SMB						**-0.02**

2. Durbl

	Low	2	3	4	High	Avg.
Small	1.08	0.53	0.85	0.69	1.60	**0.95**
2	0.22	1.01	0.54	1.01	1.55	**0.86**
3	0.72	0.92	1.12	1.29	0.85	**0.98**
4	0.80	0.44	1.05	1.02	0.53	**0.77**
Big	0.65	0.85	0.87	0.60	0.91	**0.78**
Avg.	**0.70**	**0.75**	**0.88**	**0.92**	**1.09**	
Avg HML						**0.39**
Avg SMB						**0.17**

3. Manuf

	Low	2	3	4	High	Avg.
Small	0.41	1.05	1.08	1.01	1.39	**0.99**
2	0.65	0.86	0.96	0.99	1.18	**0.93**
3	0.76	0.88	1.01	1.26	1.10	**1.00**
4	0.60	0.72	1.05	0.79	1.15	**0.86**
Big	0.74	0.61	0.72	0.81	1.04	**0.79**
Avg.	**0.63**	**0.82**	**0.97**	**0.97**	**1.17**	
Avg HML						**0.54**
Avg SMB						**0.20**

4. Enrgy

	Low	2	3	4	High	Avg.
Small	0.53	0.71	1.35	1.12	1.17	**0.97**
2	0.68	0.81	0.85	1.03	1.44	**0.96**
3	0.67	1.07	0.94	1.17	0.80	**0.93**
4	0.71	0.59	0.82	0.92	1.06	**0.82**
Big	0.30	0.49	0.91	0.83	0.84	**0.67**
Avg.	**0.58**	**0.73**	**0.98**	**1.01**	**1.06**	
Avg HML						**0.49**
Avg SMB						**0.30**

5. Chems

	Low	2	3	4	High	Avg.
Small	1.01	0.62	1.11	1.20	1.30	**1.05**
2	0.43	0.94	1.24	1.22	1.25	**1.01**
3	0.49	0.51	0.85	0.96	1.29	**0.82**
4	0.79	0.92	1.10	1.19	1.00	**1.00**
Big	0.51	0.81	0.90	0.71	0.55	**0.69**
Avg.	**0.64**	**0.76**	**1.04**	**1.05**	**1.08**	
Avg HML						**0.43**
Avg SMB						**0.35**

6. BusEq

	Low	2	3	4	High	Avg.
Small	0.31	0.43	1.47	0.78	1.76	**0.95**
2	0.64	0.56	0.85	1.17	1.06	**0.86**
3	0.60	0.88	0.67	1.12	1.51	**0.96**
4	1.16	1.12	0.86	1.31	1.31	**1.15**
Big	0.96	0.76	1.04	0.86	0.91	**0.91**
Avg.	**0.73**	**0.75**	**0.98**	**1.05**	**1.31**	
Avg HML						**0.58**
Avg SMB						**0.04**

7. Telcm

	Low	2	3	4	High	Avg.
Small	0.78	0.65	0.87	1.42	1.40	**1.02**
2	0.70	0.70	0.65	0.53	1.40	**0.80**
3	0.76	1.29	1.24	1.03	0.85	**1.03**
4	0.64	0.44	0.58	1.20	0.55	**0.68**
Big	0.30	0.50	0.44	0.35	0.64	**0.45**
Avg.	**0.64**	**0.72**	**0.76**	**0.91**	**0.97**	
Avg HML						**0.33**
Avg SMB						**0.58**

8. Utils

	Low	2	3	4	High	Avg.
Small	0.64	0.63	0.79	1.05	0.74	**0.77**
2	0.79	0.53	0.58	0.96	0.99	**0.77**
3	0.95	0.74	0.69	0.81	0.95	**0.83**
4	0.45	0.75	0.92	0.63	0.72	**0.69**
Big	0.28	0.50	0.70	0.66	0.76	**0.58**
Avg.	**0.62**	**0.63**	**0.74**	**0.82**	**0.83**	
Avg HML						**0.21**
Avg SMB						**0.19**

9. Shops

	Low	2	3	4	High	Avg.
Small	0.19	-0.16	0.74	1.02	1.16	**0.59**
2	0.38	0.93	0.71	0.97	1.06	**0.81**
3	0.98	0.78	0.72	1.03	0.94	**0.89**
4	0.81	0.71	0.86	0.92	0.68	**0.80**
Big	0.72	0.72	0.53	0.66	0.51	**0.63**
Avg.	**0.62**	**0.60**	**0.71**	**0.92**	**0.87**	
Avg HML						**0.25**
Avg SMB						**-0.04**

10. Hlth

	Low	2	3	4	High	Avg.
Small	0.40	1.21	0.98	1.51	1.60	**1.14**
2	0.70	1.02	0.70	1.10	1.18	**0.94**
3	0.71	1.00	1.36	1.12	0.88	**1.02**
4	1.18	0.80	0.91	1.24	0.81	**0.99**
Big	0.73	0.75	1.16	0.48	0.64	**0.75**
Avg.	**0.74**	**0.96**	**1.02**	**1.09**	**1.02**	
Avg HML						**0.28**
Avg SMB						**0.39**

11. Money

	Low	2	3	4	High	Avg.
Small	0.45	0.57	1.03	0.85	1.29	**0.84**
2	0.79	1.11	0.66	0.92	1.47	**0.99**
3	0.65	0.54	0.64	1.22	0.95	**0.80**
4	0.93	0.75	1.23	0.99	1.13	**1.00**
Big	0.49	0.98	0.84	0.73	0.37	**0.68**
Avg.	**0.66**	**0.79**	**0.88**	**0.94**	**1.04**	
Avg HML						**0.38**
Avg SMB						**0.16**

12. Other

	Low	2	3	4	High	Avg.
Small	0.56	1.35	1.37	1.27	1.28	**1.17**
2	0.40	1.14	1.13	1.18	0.78	**0.93**
3	0.48	0.92	1.03	0.93	0.93	**0.86**
4	0.58	0.65	0.86	0.89	1.06	**0.81**
Big	0.46	0.53	0.61	0.78	0.83	**0.64**
Avg.	**0.50**	**0.92**	**1.00**	**1.01**	**0.98**	
Avg HML						**0.48**
Avg SMB						**0.52**

Appendix F.2: Average monthly excess returns (%) for industry portfolios formed on Size (SMB) and Operating Profitability (RMW), 1963-2019.

1. NoDur

	Weak	2	3	4	Robust	Avg.
Small	0.42	0.69	0.81	1.03	1.03	**0.80**
2	0.44	0.90	0.76	0.83	0.97	**0.78**
3	0.40	0.78	0.94	0.54	0.99	**0.73**
4	0.91	0.82	0.70	0.66	1.05	**0.83**
Big	0.36	0.60	0.91	0.75	0.79	**0.68**
Avg.	**0.50**	**0.76**	**0.82**	**0.76**	**0.97**	
Avg RMW						**0.46**
Avg SMB						**0.12**

2. Durbl

	Weak	2	3	4	Robust	Avg.
Small	0.63	0.96	0.98	0.87	0.82	**0.85**
2	0.91	0.44	1.04	1.41	1.30	**1.02**
3	1.11	0.72	0.89	0.89	0.93	**0.91**
4	-0.89	0.85	0.52	0.85	0.78	**0.42**
Big	0.08	0.58	0.82	0.75	0.61	**0.57**
Avg.	**0.36**	**0.71**	**0.85**	**0.96**	**0.89**	
Avg RMW						**0.52**
Avg SMB						**0.29**

3. Manuf

	Weak	2	3	4	Robust	Avg.
Small	0.79	1.22	0.88	1.17	0.97	**1.00**
2	0.64	0.83	0.76	0.97	0.68	**0.78**
3	0.72	0.65	0.90	0.95	0.87	**0.82**
4	0.66	0.80	0.75	0.84	0.76	**0.76**
Big	0.33	0.60	0.36	0.85	0.61	**0.55**
Avg.	**0.63**	**0.82**	**0.73**	**0.95**	**0.78**	
Avg RMW						**0.15**
Avg SMB						**0.46**

4. Enrgy

	Weak	2	3	4	Robust	Avg.
Small	0.38	0.99	0.84	0.84	0.46	**0.70**
2	0.19	0.73	0.53	1.07	0.77	**0.66**
3	0.56	0.85	0.69	0.90	0.74	**0.75**
4	0.36	0.52	0.80	0.81	0.62	**0.62**
Big	0.63	0.91	0.66	0.65	0.58	**0.68**
Avg.	**0.43**	**0.80**	**0.70**	**0.85**	**0.63**	
Avg RMW						**0.21**
Avg SMB						**0.02**

5. Chems

	Weak	2	3	4	Robust	Avg.
Small	0.68	0.98	1.10	0.97	0.67	**0.88**
2	0.18	0.94	1.06	0.67	1.32	**0.83**
3	1.19	0.49	0.96	0.81	0.73	**0.84**
4	0.96	0.92	0.92	1.00	0.56	**0.87**
Big	0.35	0.72	0.59	0.54	0.54	**0.55**
Avg.	**0.67**	**0.81**	**0.92**	**0.80**	**0.76**	
Avg RMW						**0.09**
Avg SMB						**0.33**

6. BusEq

	Weak	2	3	4	Robust	Avg.
Small	0.80	1.02	1.25	0.98	1.02	**1.01**
2	0.75	0.70	0.93	0.77	1.08	**0.85**
3	0.85	1.28	0.61	0.70	1.21	**0.93**
4	0.44	0.86	0.97	1.04	0.87	**0.84**
Big	0.50	0.21	0.83	0.87	1.02	**0.69**
Avg.	**0.67**	**0.82**	**0.92**	**0.87**	**1.04**	
Avg RMW						**0.37**
Avg SMB						**0.33**

7. Telcm

	Weak	2	3	4	Robust	Avg.
Small	1.05	0.71	0.94	1.67	1.67	**1.21**
2	0.16	0.56	0.51	0.79	1.09	**0.62**
3	1.09	0.57	0.49	0.95	1.23	**0.87**
4	-0.06	0.69	0.26	0.50	1.10	**0.50**
Big	0.26	0.21	0.69	0.30	0.52	**0.40**
Avg.	**0.50**	**0.55**	**0.58**	**0.84**	**1.12**	
Avg RMW						**0.62**
Avg SMB						**0.81**

8. Utils

	Weak	2	3	4	Robust	Avg.
Small	0.65	0.72	0.75	0.78	0.74	**0.73**
2	0.55	0.50	0.66	0.68	0.91	**0.66**
3	0.76	0.78	0.81	0.89	0.91	**0.83**
4	0.47	0.68	0.59	0.63	0.69	**0.61**
Big	0.28	0.63	0.56	0.39	0.40	**0.45**
Avg.	**0.54**	**0.66**	**0.68**	**0.68**	**0.73**	
Avg RMW						**0.19**
Avg SMB						**0.28**

9. Shops

	Weak	2	3	4	Robust	Avg.
Small	0.69	0.77	0.77	0.83	0.87	**0.78**
2	0.39	0.82	0.73	0.57	1.10	**0.72**
3	0.62	1.04	1.04	0.76	0.81	**0.85**
4	0.47	0.55	0.71	0.73	0.88	**0.67**
Big	0.19	0.69	0.60	0.78	0.75	**0.60**
Avg.	**0.47**	**0.77**	**0.77**	**0.73**	**0.88**	
Avg RMW						**0.41**
Avg SMB						**0.18**

10. Hlth

	Weak	2	3	4	Robust	Avg.
Small	0.94	1.55	1.14	0.98	0.97	**1.12**
2	0.69	0.64	0.62	0.89	1.16	**0.80**
3	1.22	1.30	1.03	0.90	0.89	**1.07**
4	0.84	0.82	1.09	0.83	0.80	**0.88**
Big	0.80	0.70	0.67	0.64	0.90	**0.74**
Avg.	**0.90**	**1.00**	**0.91**	**0.85**	**0.95**	
Avg RMW						**0.05**
Avg SMB						**0.37**

11. Money

	Weak	2	3	4	Robust	Avg.
Small	-	-	-	-	-	-
2	-	-	-	-	-	-
3	-	-	-	-	-	-
4	-	-	-	-	-	-
Big	-	-	-	-	-	-
Avg.	-	-	-	-	-	
Avg RMW						-
Avg SMB						-

12. Other

	Weak	2	3	4	Robust	Avg.
Small	0.64	0.90	1.21	0.94	1.04	**0.95**
2	0.45	0.91	0.54	0.74	0.94	**0.72**
3	0.39	0.83	1.16	0.65	0.96	**0.80**
4	0.49	0.51	0.59	0.69	0.97	**0.65**
Big	0.62	0.98	0.37	0.15	0.61	**0.55**
Avg.	**0.52**	**0.82**	**0.77**	**0.63**	**0.90**	
Avg RMW						**0.38**
Avg SMB						**0.40**

Appendix F.3: Average monthly excess returns (%) for industry portfolios formed on Size (SMB) and Investment (CMA), 1963-2019.

1. NoDur

	Cons	2	3	4	Aggr	Avg.
Small	0.71	0.69	1.18	0.79	0.38	**0.75**
2	0.50	0.74	0.86	0.68	0.65	**0.68**
3	0.92	0.89	0.91	0.77	0.47	**0.79**
4	0.77	0.78	0.72	0.73	0.89	**0.78**
Big	0.86	0.89	0.61	0.81	0.68	**0.77**
Avg.	**0.75**	**0.80**	**0.86**	**0.76**	**0.61**	
Avg CMA						**0.14**
Avg SMB						**-0.02**

2. Durbl

	Cons	2	3	4	Aggr	Avg.
Small	1.02	0.79	0.98	0.80	0.44	**0.81**
2	1.30	1.15	0.61	1.32	0.32	**0.94**
3	1.04	0.73	1.05	0.67	0.55	**0.81**
4	0.50	0.51	0.39	0.68	0.84	**0.58**
Big	0.65	0.51	0.54	0.94	0.52	**0.63**
Avg.	**0.90**	**0.74**	**0.71**	**0.88**	**0.53**	
Avg CMA						**0.37**
Avg SMB						**0.18**

3. Manuf

	Cons	2	3	4	Aggr	Avg.
Small	0.95	1.17	1.19	0.96	0.70	**0.99**
2	0.83	0.90	0.72	0.68	0.61	**0.75**
3	1.02	1.03	0.68	0.83	0.64	**0.84**
4	0.78	0.78	0.83	0.82	0.61	**0.76**
Big	0.73	0.59	0.69	0.60	0.52	**0.63**
Avg.	**0.86**	**0.89**	**0.82**	**0.78**	**0.62**	
Avg CMA						**0.25**
Avg SMB						**0.36**

4. Enrgy

	Cons	2	3	4	Aggr	Avg.
Small	0.47	0.98	0.75	0.53	0.23	**0.59**
2	0.94	0.21	0.64	0.50	0.70	**0.60**
3	0.36	0.90	0.50	0.45	0.68	**0.58**
4	0.76	0.64	0.80	0.71	0.55	**0.69**
Big	0.35	0.74	0.76	0.78	0.53	**0.63**
Avg.	**0.58**	**0.70**	**0.69**	**0.59**	**0.54**	
Avg CMA						**0.04**
Avg SMB						**-0.04**

5. Chems

	Cons	2	3	4	Aggr	Avg.
Small	1.37	0.97	1.14	1.12	0.47	**1.01**
2	0.92	1.14	0.72	0.73	0.39	**0.78**
3	0.76	1.07	0.89	0.82	0.58	**0.82**
4	0.47	0.84	1.10	0.74	0.51	**0.73**
Big	0.38	0.67	0.44	0.71	0.36	**0.51**
Avg.	**0.78**	**0.94**	**0.86**	**0.82**	**0.46**	
Avg CMA						**0.32**
Avg SMB						**0.50**

6. BusEq

	Cons	2	3	4	Aggr	Avg.
Small	1.14	1.45	1.56	0.94	0.37	**1.09**
2	0.85	0.83	1.01	0.81	0.48	**0.80**
3	1.28	1.21	1.00	0.64	0.96	**1.02**
4	1.06	1.18	0.86	1.01	0.69	**0.96**
Big	1.09	0.80	0.74	0.89	0.83	**0.87**
Avg.	**1.08**	**1.09**	**1.03**	**0.86**	**0.66**	
Avg CMA						**0.42**
Avg SMB						**0.22**

7. Telcm

	Cons	2	3	4	Aggr	Avg.
Small	1.29	1.33	1.61	0.44	0.80	**1.10**
2	0.84	0.96	0.53	0.21	0.63	**0.63**
3	1.01	1.11	1.09	0.99	0.58	**0.96**
4	0.61	0.68	0.41	0.61	0.70	**0.60**
Big	0.35	0.48	0.65	0.63	0.86	**0.60**
Avg.	**0.82**	**0.91**	**0.86**	**0.58**	**0.71**	
Avg CMA						**0.10**
Avg SMB						**0.50**

8. Utils

	Cons	2	3	4	Aggr	Avg.
Small	0.80	0.73	0.63	0.70	0.73	**0.72**
2	0.64	0.64	0.72	0.70	0.52	**0.64**
3	0.93	0.83	0.76	0.66	0.95	**0.83**
4	0.79	0.62	0.64	0.58	0.34	**0.59**
Big	0.73	0.65	0.54	0.33	0.36	**0.52**
Avg.	**0.78**	**0.70**	**0.66**	**0.59**	**0.58**	
Avg CMA						**0.20**
Avg SMB						**0.19**

9. Shops

	Cons	2	3	4	Aggr	Avg.
Small	0.93	0.81	0.75	0.89	0.55	**0.79**
2	0.44	0.92	1.08	0.85	0.68	**0.80**
3	1.01	1.06	0.84	0.87	0.72	**0.90**
4	0.48	0.67	0.81	0.64	0.65	**0.65**
Big	0.77	0.71	0.72	0.85	0.65	**0.74**
Avg.	**0.73**	**0.84**	**0.84**	**0.82**	**0.65**	
Avg CMA						**0.08**
Avg SMB						**0.05**

10. Hlth

	Cons	2	3	4	Aggr	Avg.
Small	1.19	1.36	1.56	1.17	0.62	**1.18**
2	0.98	1.04	0.98	1.03	0.72	**0.95**
3	1.23	1.54	0.76	1.05	0.99	**1.11**
4	1.18	1.21	1.01	0.55	0.74	**0.94**
Big	0.81	0.90	0.85	0.53	0.28	**0.67**
Avg.	**1.08**	**1.21**	**1.03**	**0.87**	**0.67**	
Avg CMA						**0.41**
Avg SMB						**0.51**

11. Money

	Cons	2	3	4	Aggr	Avg.
Small	-	-	-	-	-	-
2	-	-	-	-	-	-
3	-	-	-	-	-	-
4	-	-	-	-	-	-
Big	-	-	-	-	-	-
Avg.	-	-	-	-	-	
Avg CMA						-
Avg SMB						-

12. Other

	Cons	2	3	4	Aggr	Avg.
Small	0.84	1.29	0.96	0.85	0.40	**0.87**
2	1.18	0.74	0.85	0.85	0.75	**0.87**
3	1.15	0.92	1.04	0.80	0.55	**0.89**
4	0.68	0.92	0.93	0.96	0.27	**0.75**
Big	0.84	0.63	0.51	0.42	0.29	**0.54**
Avg.	**0.94**	**0.90**	**0.86**	**0.77**	**0.45**	
Avg CMA						**0.49**
Avg SMB						**0.33**

Appendix F.4: Average monthly excess returns (%) for industry portfolios formed on Size (SMB) and Momentum (UMD), 1926-2019.

1. NoDur

	Down	2	3	4	Up	Avg.
Small	0.43	0.81	1.27	1.01	1.43	**0.99**
2	0.15	0.86	0.94	0.93	1.39	**0.86**
3	0.43	0.74	1.06	1.06	0.83	**0.83**
4	0.31	0.60	0.94	0.85	1.03	**0.75**
Big	0.17	0.56	0.50	0.89	0.99	**0.62**
Avg.	**0.30**	**0.71**	**0.94**	**0.95**	**1.14**	
Avg UMD						**0.84**
Avg SMB						**0.37**

2. Durbl

	Down	2	3	4	Up	Avg.
Small	0.41	0.88	1.35	1.25	1.77	**1.13**
2	0.52	0.31	1.27	0.88	1.12	**0.82**
3	0.54	1.10	0.96	1.02	1.51	**1.03**
4	0.27	0.37	0.99	0.62	1.09	**0.67**
Big	-0.06	0.71	0.83	0.59	1.17	**0.65**
Avg.	**0.33**	**0.67**	**1.08**	**0.88**	**1.33**	
Avg UMD						**1.00**
Avg SMB						**0.48**

3. Manuf

	Down	2	3	4	Up	Avg.
Small	0.99	1.13	0.85	1.19	1.44	**1.12**
2	0.64	0.59	0.95	1.03	1.26	**0.90**
3	0.57	0.90	1.03	1.00	1.18	**0.94**
4	0.56	0.70	0.72	0.76	1.15	**0.78**
Big	0.61	0.68	0.65	0.76	0.91	**0.72**
Avg.	**0.67**	**0.80**	**0.84**	**0.95**	**1.19**	
Avg UMD						**0.51**
Avg SMB						**0.40**

4. Enrgy

	Down	2	3	4	Up	Avg.
Small	0.65	0.72	0.87	0.92	1.09	**0.85**
2	0.58	0.63	1.11	0.82	1.29	**0.89**
3	0.59	0.86	1.11	0.95	0.97	**0.89**
4	0.59	0.80	0.85	0.73	0.71	**0.74**
Big	0.42	0.90	0.73	0.77	0.75	**0.71**
Avg.	**0.57**	**0.78**	**0.93**	**0.84**	**0.96**	
Avg UMD						**0.40**
Avg SMB						**0.14**

5. Chems

	Down	2	3	4	Up	Avg.
Small	0.72	1.04	1.41	1.42	1.42	**1.20**
2	0.61	0.85	1.16	1.12	1.25	**1.00**
3	0.77	0.50	0.76	1.10	0.93	**0.81**
4	1.07	0.82	0.81	0.87	1.21	**0.95**
Big	0.64	0.75	0.68	0.69	0.95	**0.74**
Avg.	**0.76**	**0.79**	**0.97**	**1.04**	**1.15**	
Avg UMD						**0.39**
Avg SMB						**0.46**

6. BusEq

	Down	2	3	4	Up	Avg.
Small	0.71	1.04	1.62	1.63	1.43	**1.29**
2	0.56	0.76	0.73	0.96	1.16	**0.83**
3	0.00	0.93	0.30	1.09	1.38	**0.74**
4	0.36	0.71	1.08	0.99	1.68	**0.97**
Big	0.02	0.69	0.83	0.89	1.43	**0.77**
Avg.	**0.33**	**0.83**	**0.91**	**1.11**	**1.42**	
Avg UMD						**1.08**
Avg SMB						**0.51**

7. Telcm

	Down	2	3	4	Up	Avg.
Small	0.82	0.75	1.02	1.07	1.38	**1.01**
2	1.32	0.54	0.77	1.10	0.79	**0.90**
3	0.21	1.43	0.28	0.98	1.37	**0.85**
4	0.59	0.70	0.74	0.77	0.92	**0.74**
Big	-0.03	0.49	0.37	0.74	0.47	**0.41**
Avg.	**0.58**	**0.78**	**0.63**	**0.93**	**0.99**	
Avg UMD						**0.41**
Avg SMB						**0.60**

8. Utils

	Down	2	3	4	Up	Avg.
Small	0.77	0.86	0.85	0.66	1.41	**0.91**
2	0.60	1.02	0.80	0.79	0.85	**0.81**
3	0.80	0.89	0.71	0.92	1.11	**0.89**
4	0.91	0.52	0.71	0.75	0.95	**0.77**
Big	0.33	0.45	0.72	0.59	0.44	**0.51**
Avg.	**0.68**	**0.74**	**0.76**	**0.74**	**0.95**	
Avg UMD						**0.27**
Avg SMB						**0.40**

9. Shops

	Down	2	3	4	Up	Avg.
Small	0.56	0.89	1.09	0.99	1.43	**0.99**
2	0.45	0.94	0.85	0.94	1.50	**0.94**
3	0.17	0.48	1.01	0.88	1.38	**0.78**
4	0.86	0.39	0.78	0.79	0.90	**0.74**
Big	0.32	0.55	0.54	0.75	1.09	**0.65**
Avg.	**0.47**	**0.65**	**0.85**	**0.87**	**1.26**	
Avg UMD						**0.79**
Avg SMB						**0.34**

10. Hlth

	Down	2	3	4	Up	Avg.
Small	0.85	1.18	1.25	1.44	1.58	**1.26**
2	0.43	0.91	1.13	1.15	1.42	**1.01**
3	0.70	1.13	0.73	1.20	1.46	**1.04**
4	0.97	0.67	1.15	1.25	0.99	**1.01**
Big	0.49	0.70	0.64	0.62	1.14	**0.72**
Avg.	**0.69**	**0.92**	**0.98**	**1.13**	**1.32**	
Avg UMD						**0.63**
Avg SMB						**0.54**

11. Money

	Down	2	3	4	Up	Avg.
Small	0.58	0.76	1.01	1.17	1.08	**0.92**
2	1.22	0.81	1.12	0.80	1.10	**1.01**
3	0.05	0.86	0.90	0.87	1.26	**0.79**
4	0.46	0.76	0.71	0.85	1.14	**0.78**
Big	0.41	0.54	0.73	0.93	0.78	**0.68**
Avg.	**0.55**	**0.74**	**0.89**	**0.92**	**1.07**	
Avg UMD						**0.52**
Avg SMB						**0.24**

12. Other

	Down	2	3	4	Up	Avg.
Small	0.45	0.93	1.45	1.08	1.47	**1.08**
2	0.24	1.04	1.12	1.10	1.24	**0.95**
3	0.39	0.56	0.86	0.84	1.10	**0.75**
4	0.40	0.60	0.71	0.87	1.08	**0.73**
Big	0.19	0.53	0.44	0.65	0.94	**0.55**
Avg.	**0.33**	**0.73**	**0.92**	**0.91**	**1.17**	
Avg UMD						**0.83**
Avg SMB						**0.53**