Principal Portfolios Performance

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Abstract

This thesis examines the cross-sectional dynamic performance of the US stock markets through Principal Components analysis (PCA). We examine the annual and semi-annual performance, from 1928 to 2015, of the portfolios obtained from the top five principal components from past returns. These capture seventy percent of the variation in assets returns. The first principal component has over ninety percent annual correlation with the market. The second, third, fourth and fifth principal components have persistent characteristics different from the market. A Sharpe Ratio of 0.79 and maximum drawdown of 0.27 could be obtained by investing in a combination of the principal portfolios, compared to a Sharpe ratio of 0.40 for the market and a maximum drawdown of 0.80. The four-factors (market, size, value and momentum) and betting against Beta regressions show a significantly positive alpha, whence portfolio performance cannot be explained by these factors. Importantly, the composite portfolios exposure to industry sectors that are most affected by downturns tends to decline before the downturns take place. Chapter 1

Introduction

Two of the most important goals for investors when allocating capital among different assets are (i) to earn consistent returns that at a minimum protect the purchasing power of one's saving, and (ii) to avoid permanent loss of capital or limit this risk i.e. avoiding large decrease in one's capital. To achieve these goals, investors' approaches can generally be categorized into either passive or active investing. While both approaches have received criticism, the active approach received substantially more critics especially among academics. "Since the value weighted portfolio of active funds produces close to zero in gross (pre-expense) returns, estimated on the net (post-expense) returns realized by investors is negative by about the amount of fund expenses." (Fama and French, 2010).

Examining the financial Market historical returns and the re-occurrence of economic crises in developed and emerging markets shows that bubbles and busts are an inherent trait in the financial markets (Allen and Gale, 2000). Markets drawdowns were approximately 85, 56, 54 and 45 percent in 1929, 1973, 2000 and 2008 respectively, which shows that overall achieving the investors' second goal has been a goal that many investors from both active and passive camps have failed to achieve.

Due to the inclination of uncorrelated assets to generate superior risk-adjusted returns when put together in a portfolio, in addition to the capacity of long short strategies to limit drawdowns, we examine the application of principal component analysis to the US stock market from 1927 to 2015. PCA is one of the best-known techniques in multivariate data analysis. Its range of applications has expanded dramatically with the advent of computers and it has been applied in a wide variety of areas for the last 50 years. The capacity of PCA to decompose correlated variables into uncorrelated variables makes it attractive to use in analysing complex structures. To assess the principal components (i)performance (ii)potential in achieving investors two goals and (iii) to identify persistent patterns in stocks returns, we compute PCA on an annual and semi-annual basis for common stocks returns time series available from the Center for Research in Security Prices database ¹ (CRSP)². We study the five components corresponding to the largest five eigenvalues.

Each component has specific weight for each asset, some are negative and others positive. We examine each component, its positive side and negative side separately. We calculate these components' monthly returns, overall and annual volatility, get their weights annual and semi-annual distribution, calculate the drawdowns time series, run regressions to compute these components' exposure to the four Fama-French factors (Market, Size, Value and momentum) and betting against beta factor, calculate overall correlation and annual correlation time series. We also calculate their overall accumulation value and 10-years consecutive accumulation value time series from 1928 to 2015, calculate their Sharpe ratio, construct equal weight composite portfolios out of these total, long and short sides. We repeat the same analysis for these as for the single components in addition to calculating Sharpe ratios over consecutive ten year windows from 1927-2015. We also examine single components and composite portfolios exposure to industry sectors before, during and after recessions. We calculate returns after accounting for transaction costs of 0.5 and 1 percent. No studies have examined the US stock market principal components for the period 1927-to-2015, and also no previous work has decomposed the principal components into total, long and short side

¹http://www.crsp.com/main-menu/why-crsp

²http://www.crsp.com/products/research-products/crsp-us-stock-databases

and analysing each side separately.

We find out that these components have attractive distinct characteristics. First of all, they have zero correlation in-sample and low correlation out-of-sample. The first five principal components explain 70 percent of the variability in assets returns. The first principal component (PC1) correlation with the market is 0.90. The second principal (PC2) component has a Sharpe ratio of 0.60 and 0.57 on annual and semi-annual basis respectively.

After excluding PC1 due to its high correlation with the market, we combine sets of six sides either four long and two short or three long and three short on equal weight basis in search for strategies that can be used to construct composite portfolios with high potential. We find out that PC2 annual and semi-annual total and long sides, PC5 annual total, long and short sides, PC3 annual short side and PC4 annual and semi-annual total and short sides have the potential when combined together in a set of six in a composite portfolio to generate better than the market risk-adjusted returns. These have over 0.78 Sharpe ratio which drops to 0.62 after accounting for transaction costs over eighty eight years, which is 50% better than the market's Sharpe ratio. These composite portfolios have a maximum drawdown of 27 % compared to 80% for the market.

Four factor model explains 27 percent of the variability of these composite portfolio returns. They have statistically significant alpha of over 0.35 percent. They have maximum statistically significant exposure of 0.27, 0.11 and 0.09 to market, value and momentum factors. The size factor is not statistically significant. Due to their low market beta, we run regression against betting against beta factor as well, which captures less than 0.5 percent of the variability in their returns.

PCA has been used widely in Finance, it has been used to identify common factors in international bond returns Driessen et al. (2003) and Pérignon et al. (2007). It also has also been used in subjects such as arbitrage pricing theory Chamberlain and Rothschild (1982).

Avellaneda and Lee (2010) look at PCA in the context of generating mean reversion trading strategies signal. They show that PCA of the correlation matrix for the broad equity market in the U.S. gives rise to risk-factors that have economic significance because they can be interpreted as long-short portfolios of industry sectors. They look at the first 15 eigenvectors and eigenvalues over the period 1997-2007. Partovi et al. (2004) show how finding an efficient portfolio can simplified by looking at the principal portfolios which are basically the principal components, because instead of looking at a large number of correlated variables we look at a smaller set of uncorrelated portfolios.

Kind (2013) builds on Partovi and Caputo's work (2004), he uses PCA to construct uncorrelated principal portfolios, derive general formulas for equal weights, minimum variance and risk parity principal portfolios. He shows how to construct optimization problems in these cases, his back testing shows risk diversification does outperform nominal diversification. Meucci (2010) followed Partovi and Caputo (2004) approach by transforming a returns time series set in which there were a large number of correlated assets into principal portfolios representing uncorrelated risk sources inherent in the original assets.

Lohre et al. (2012) and Lohre et al. (2014) adopt Meucci framework in order to get maximum diversification in equity and multi-asset classes respectively. Their approach was to equally distribute capital across principal portfolios to well diversify its overall risk. They named this strategy " diversified risk parity ".

Eleutério et al. (2014) use geometric technique involving correlation to analyse returns

time series, and find that best performance portfolios over a period (1990 - 2008) are associated with some of the small eigenvalue subspaces. However the number of companies they analysed was relatively small in comparison to the total number of companies.

Connor and Korajczyk (1993) use a new approach to testing for the appropriate number of factors in an approximate factor model of asset returns. They use asymptotic principal components. They argue for three to six factors capturing most of the variability when testing five years window of returns time series.

Fenn et al. (2011) apply PCA to examine the correlation in various asset classes: twenty five developed market equity indices, three emerging market equity indices, four corporate bond indices, twenty government bond indices, fifteen currencies, nine metals, four fuel commodities, and eighteen other commodities. They claim that increases in the variance explained by PC1 implied that there is a pattern in the returns variation in different financial assets. Moreover, they highlight that the variance explained by the first component could be either the result of increases in the correlations among a few assets classes or a market-wide correlation. While one can simply move capital to less correlated assets to decrease first case impact on the diversification, it is much more difficult to reduce risk by diversifying across different assets if it is a market-wide correlation increase.

The rest of the paper is organized as follows. Chapter 2 explains how we apply PCA, describe our data set, and how we reorganize and reshape our data into annual and semiannual bases, it outlines the main steps taken to construct composite portfolios. Chapter 3 contains results, our analysis and discussion. Chapter 4 contains our conclusion. Chapter 5 contains appendices with industry exposure tables, correlation table, shows how we calculate our monthly returns. Chapter 2

Method

2.1 Approach

The number of publicly traded firms in the United States in 2016 was 3833. To analyse such a large dataset, professional investors and academics have sorted these stocks based on many characteristics, including: size, value and industry sectors. One of the most important characteristics is the covariance between assets returns which was highlighted by Markowitz fifty years ago when he introduced the mean-variance approach to build efficient portfolios. One of the key points of his approach is the role of the covariance between different stocks can play to reduce the portfolio overall variance when constructing investment portfolios. Hence it is vital to explore if there are any dominant persistent traits of this cross-sectional quantity. We take an in-depth look at the covariance between stocks returns in the US market.

Principal Components Analysis (PCA) is a well known technique used for multivariate data analysis (Jolliffe, 1986). Some of the PCA uses include: simplification, dimension reduction, outliers detection, classification and prediction. PCA transforms the data by projecting it onto a set of orthogonal axes. It extracts a set of features from a high dimensional data set with the goal to keep as much information as possible but with a low number of factors. PCA entails calculating the covariance matrix for a set of data for a number of variables and finding eigenvalues and eigenvectors for this covariance matrix. The first component which is the first eigenvector corresponds to the largest eigenvalue. It is the dimension that captures the largest amount of variability in the data, the second principal components corresponds to the second largest eigenvalue which captures the largest possible amount of variability that is orthogonal to the first component, and so on for each subsequent component. Each principal component is a linear combination of the original variables, in which the loadings indicate the relative significance of the variable in the component.

We use PCA to analyse stock returns. Connor and Korajczyk (1993) argue that the first three to six components contain most of the information about returns time series.

For non-January months, a one-factor or two-factor model seems adequate to describe stock returns. Including January, up to six factors are necessary to provide an adequate description. Since January mean returns and variances are unusually large, and many interesting asset-pricing phenomena are concentrated in this month, we argue for a three- to six-factor model.

Accordingly, and since these eigenvalues are essentially the variance of each eigenvector. We focus in our analysis on the first five components corresponding to the largest five eigenvalues, this is because these contain substantial amount of information about our data set. The remaining eigenvalues are small, indicating that there is less chance of producing sufficient variation and interactions during different market conditions.

The main steps involved in constructing our portfolios are as follows:

- (i) . Creating semi-annual and annual data-tables of daily returns,
- (ii) Conducting annual and semi-annual Principal Components Analysis over period 1927-2015,

- (a) Calculate the annual and semi-annual covariance matrix.
- (b) Compute eigenvalues and eigenvectors for these covariance matrices.
- (iii) . Calculate next period returns for these eigenvectors i.e. Principal Portfolios.
- (iv) . Analyse single principal portfolios returns time series.
- (v) . Construct composite portfolios out of these single principal portfolios based on their correlation, Sharpe ratio.

Our main focus is on the largest five eigenvalues and their corresponding eigenvectors.

2.2 Data

We use the CRSP daily and monthly databases in our research. Our data analysis covers the period from 1927-01-01 to 2015-12-31. We calculate total returns: capital appreciation and dividend as shown in (5.1). From the CRSP database We extracted columns with the heading:

- PERMNO: Permanent Number of Securities in Index List.
- Caldt: Calendar date for which daily or monthly returns data apply.
- Shr: The unadjusted number of publicly held shares on NYSE, NYSE MKT, NASDAQ, and Arca exchanges, recorded in 1000s.
- SCL: 2-digit code, most recently known as of end of period. First digit describes the type of security; second digit provides further security or company detail.
- SIC: The SIC code is used to group companies with similar products or services at the end of the period reported. The Standard Industrial Classification Manual contains descriptions of categories recognized by the US Government. SIC Code is an integer between 100 and 9999. The first two digits refer to a major group. The first three digits refer to an industry group. All four digits indicate an industry.
- Prc:
 - Daily: The last non-missing daily closing price or bid/ask average of a security. If a price is unavailable, the number in the price field is replaced with a bid/ask average (marked by a leading dash).
 - Monthly: The last non-missing closing price of a security for the last trading day of the month. If unavailable, the number in the price field is replaced with a bid/ask average (marked by a leading dash).
- Ret:

- Daily: Daily change in the total value of an investment, using prices or bid/ask averages if prices not available. Dividends are reinvested on the Ex-date.
- Monthly: Month-end to month-end change in total investment of a security, with ordinary dividends reinvested at the month-end.
- Shrcd: 2-digit code as of end of period. The First digit describes the type of security, the second digit provides further security or company detail.
- Odivamt: Ordinary cash dividends paid during the period, adjusted to beginning of period basis.

We keep all CRSP all common stocks that have share code of 10 or 11 i.e. ordinary equity, incorporated in the US and listed on the NYSE, AMEX or NASDAQ. From this data we create table that has three columns: PERMNO, Date, total excess returns and total market capitalization. We use this table to do Principal Components Analysis and also to calculate portfolios returns on a monthly and daily basis.

2.3 Principal Components Computation

2.3.1 Annual and Semi-Annual Data Tables

For our annual tables we create a single data table for each year starting from 1927 to 2015, for a total of 89 tables. We reshape these data so that each column corresponds to the returns of a stock for that year, the number of rows in each table is the number of trading days in that year.

We exclude micro-cap stocks, as recently defined by U.S. Securities and Exchange Commission¹ as " companies with a market capitalization of less than \$250 or \$300 million." The rational for such an exclusion as Fama and French (2008) point out:

First, though microcaps are on average only about 3% of the market cap of the NYSE-Amex-NASDAQ universe they account for about 60% of the total number of stocks. Second, the cross-section dispersion of anomaly variables is largest among micro-caps so they typically account for more than 60% of the stocks in extreme sort portfolios.

Also Hou et al. (2017) add: "Due to high transaction costs and illiquidity anomalies in microcaps are unlikely to be exploitable in practice." .

At each period (annual and semi-annual) we sort companies by their total market capitalization and remove all firms that sum up to 3% of market capitalization. Table (3.5) shows the total number of publicly traded companies by year and the total number we consider in our analysis after excluding microcaps. Notice also that the number of microcap traded companies was approximately

¹https://www.sec.gov/reportspubs/investor-publications/investorpubsmicrocapstockhtm. html

Year	Total	Excluding Micrcaps	Percentage considered
1927	594	318	0.54
1928	640	336	0.52
1929	728	337	0.46
1930	748	334	0.45
1931	739	317	0.43
1932	719	296	0.41
1933	703	320	0.46
1934	694	345	0.10
1935	712	355	0.50
1036	734	307	0.50
1037	764	302	0.54
1038	760	403	0.51
1020	709	405	0.52
1040	779	400	0.55
1940	790	419	0.54
1941	780	423	0.54
1942	784	442	0.56
1943	799	472	0.59
1944	815	517	0.63
1945	835	563	0.67
1946	886	581	0.66
1947	919	597	0.65
1948	941	605	0.64
1949	966	604	0.63
1950	988	628	0.64
1951	1006	631	0.63
1952	1021	626	0.61
1953	1033	614	0.59
1954	1032	614	0.59
1955	1049	604	0.58
1956	1044	597	0.57
1957	1065	579	0.54
1958	1056	607	0.57
1959	1072	617	0.58
1960	1109	626	0.56
1961	1134	640	0.56
1962	1991	790	0.40
1963	2063	888	0.43
1964	2102	907	0.43
1965	2151	985	0.46
1966	2101	08/	0.40
1967	2100	1199	0.40
1069	2210	1122	0.51
1000	2200	1209	0.04
1969	2309	1142	0.49
1970	2373	1091	0.46
1971	2467	1141	0.46

Table 2.1: Number of companies of common stocks in the CRSP database, including and excluding micro-caps

 $\leq 50\% \pm 5\%$ of the total number publicly traded companies and their number increases to become 77 % at the height of the tech-boom, and decreased afterwards to that be on average 65 %.

For our semi-annual analysis, we have two tables for each year. One for the first six months (January-June) and one for the last six months (July-December). We have 178 tables. The format of these tables is the same as for annual table, so that columns contain returns corresponding to a single stock, the only difference being that the number of rows in the semi-annual tables is half the number of rows in the annual tables.

We use the PERMNO number provided by CRSP as our stocks identifier. Since we

record returns of these principal components at the next period (either next year or the next 6 month) we only keep stocks that are trading in the last ten days December for annual tables, and June or December for semi-annual tables respectively. We replace all missing returns put as (-99, -88, -77, -66, -55) by NA's. We remove columns that have more than 75 and 50 missing prices in each of the annual and semi-annual daily table respectively.

2.3.2 Principal Components

We compute the covariance matrix for each annual and semi-annual table using the cov function in the R-programming language, then calculate the eigenvalues and eigenvectors for each covariance matrix using the eigen function. Apart from the method we used to perform principal component analysis, it is possible to perform it by using prcomp function. While both produce the same results the only difference we have noticed is that for some components the weights sign is reversed. Loadings of each eigenvector are considered as the weight the principal components analysis assigns to the corresponding securities. For each component we have three sides:

- Long (LO): containing positive weights.
- Short (SH): containing negative weights
- Total (TOT): containing both negative and positive weights.

In addition to controlling for volatility, we measure the overall exposure on annual and semi-annual basis to see whether we have an overall long or short position. If the overall sum is negative, we multiply all weights by -1 in order to have an overall long position. This also helps as another step to ensure that the eigenvalues and eigenvectors calculated using different methods can be reconciled to have the same over all exposure. As a risk control measure and in order to reduce volatility, we also have an absolute value (10 %) weight constraint that we apply on annual and semi-annual basis, so if the weight is -20 % it becomes -10 %, and if it is 30 % it becomes 10 %.

In the principal portfolio environment, all the principal portfolios are uncorrelated and therefore the variances are additive. The total variance of a linear combinations of principal portfolios is simply the sum of the variances of all principal portfolios. The ratio of individual principal portfolio variance to the total variance is then in the range of 0 to 1, and they sum up to 1. To estimate the resultant volatility for a portfolio we have:

$$\operatorname{Var}(a_1X_1 + \dots + a_nX_n) = \sum a_i^2 \operatorname{Var}(X_i) + \sum 2a_i a_j \operatorname{Cov}(X_iX_j)$$

We will assume equal weight to each component in our composite portfolio, for example if we have five components, each will have 0.2 weight. Securities weight for each component is decided by the PCA process, what we do is merely constructing equal weight portfolio from different components.

$$\operatorname{Portfolio} = \frac{1}{n} \left(pc_1 + pc_2 + pc_3 + pc_4 + \dots + pc_n \right)$$

$$\Rightarrow \operatorname{Var}(\operatorname{Portfolio}) = \operatorname{Var}\left(\frac{1}{n} (pc_1 + pc_2 + pc_3 + pc_4 + \dots + pc_n)\right)$$

since covariance between principal componets is zero

$$= \frac{1}{m^2} \left(\operatorname{Var}(pc_1) + \operatorname{Var}(pc_2) + \operatorname{Var}(pc_3) + \operatorname{Var}(pc_4) + \dots + \operatorname{Var}(pc_n) \right)$$

$$= \frac{1}{n^2} \left(\operatorname{Var}(pc_1) + \operatorname{Var}(pc_2) + \operatorname{Var}(pc_3) + \operatorname{Var}(pc_4) + \dots + \operatorname{Var}(pc_n) \right)$$
$$= \frac{1}{n^2} (n \operatorname{Var}(pc)) = \frac{1}{n} \operatorname{Var}(pc)$$

We want our portfolio's volatility to be approximately 10%For equal weight portfolio of five components we have n=5

$$\Rightarrow (0.1)^2 = (0.2)(Var(pc)) \Rightarrow Var(pc) = \frac{0.01}{0.2} = 0.05$$

 $\Rightarrow \text{Volatility}(\text{pc}) = \sqrt[2]{Variance} = \sqrt[2]{0.05} = 0.2236068 = 22.36\%$

Because principal components are identified up to a scaling factor, we normalize each component so that it has, in sample, the same volatility, conventionally, set at 22.36% per year.

We have five principal components, each has three sides (Total, Long and Short) i.e. the total number of strategies that we calculate and record their returns are 30 strategies. Our returns time series start at January 1928 to November 2015. Each strategy has 1055 rows, each row corresponding to the monthly return of that strategy. We combine these strategies returns into one table. Each column corresponds to a specific strategy (a component side).

2.4 Composite Portfolios

Long-short equity strategies (LS) are known to generate higher risk-adjusted returns with lower volatility than long only strategies. They have become a core strategy for many institutional investors. The reduction in volatility comes mainly from the negative exposure to the market achieved by the short side. Some investors attempt to construct optimal LS portfolios by combining a short only portfolio with an independently generated long-only portfolio. Others add the market neutrality condition to their portfolio construction and implementation, or build 130/30 long short portfolios to add some leverage to their portfolio or choose the short and long sides in such way to have a desired exposure to an industry sector or a country or any other factor. Feghali et al. (2013) argue that LS allow investors to generate alpha through three components: stock selection, passive market exposure and tactical market exposure. By seeking to explicitly and individually control all three major sources of LS returns, LS strategies represent enable for obtaining better risk-adjusted returns i.e. better Sharpe ratio.

We have five components, each has three sides. We also do PCA on annual and semiannual basis, so the total number of strategies is 30: 10 total, 10 long and 10 short. In our search to find persistent patterns, we build long-short portfolios using these thirty strategies according to these steps:

- 1. Due to PC1' high correlation with the market we exclude the annual and semi-annual PC1 total, long and short sides.
- 2. We define our long candidates set by all the sides that have positive Sharpe ratio from Table (3.2). We have 16 strategies in this set. Their Sharpe ratio ranges from 0.21 to 0.60, as shown in table (3.5b).
 - (a) Annual: a-PC2TOT, a-PC2LO, a-PC3TOT, a-PC3LO, a-PC4TOT, a-PC4LO, a-PC5TOT, a-PC5LO.
 - (b) Semi-annual: m6-PC2TOT, m6-PC2LO, m6-PC3TOT, m6-PC3LO, m6-PC4TOT, m6-PC4LO, m6-PC5TOT, m6-PC5LO.

Where: a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC. LO: stands for long side (includes only positive weights).

- 3. We define our short candidates set by all strategies that have negative Sharpe ratio. Their Sharpe ratio ranges from -0.35 to -0.19, as shown in table (3.5b). We have eight strategies in our short strategies pool; four are annual strategies and four semi-annual.
 - (a) Annual: a-PC2SH, a-PC3SH, a-PC4SH, a-PC5SH.
 - (b) Semi-Annual: m6-PC2SH, m6-PC3SH, m6-PC4SH, m6-PC5SH.

SH: stands for short (includes only negative weights)

- 4. Table (3.5b) Shows that all long candidates have a various positive exposure to market, this positive exposure decreases as we move from PC2 to PC5 as shown in table (3.2). These strategies have distinct exposure to the remaining factors.
- 5. For short candidates, most strategies have negative exposure to market, SMB and Momentum, and positive exposure HML i.e. to Value stocks. Some of these short strategies exposures are not statistically significant at 0.05 level.
- 6. Annual PC2, annual PC2 Long side, annual PC5, semi-annual PC2 and semi-annual PC4 long side all have relatively high Sharpe ratios (0.60, 0.48, 0.49, 0.57, 0.38) respectively and a low cross correlation as table (3.7) shows.
- 7. Composite portfolios are long short portfolios which consist mainly of 6 components (strategies):
 - i) 4 long portfolios and 2 short, or
 - ii) 3 long portfolios and 3 short
- 8. We sort the resulting portfolios by Sharpe ratio in decreasing order, and analyse the members of portfolios with Sharpe ratio over 0.65.

- 9. To identify composite portfolio candidates, we compute and record the frequency of strategies in step 8.
- 10. From the set in step 9, we keep portfolios which have the following characteristics: maximum drawdown ≤ 0.26 , accumulated value > 200, minimum accumulated value over a period 10 years is 1%, Market Beta<0.4, regression R² <0.4, a statistically significant alpha of at least 0.3 (t_{value} >3.5).

Chapter 3

Results and Discussion

3.1 Single Components Analysis

3.1.1 Weights Change Time Series Statistics

Component	Mean	Std
Pc1	0.59	0.76
Pc2	1.97	0.73
Pc3	2.02	0.45
Pc4	2.00	0.27
Pc5	2.03	0.21

Table 3.1: The sum of squares of annual weight changes W_t - W_{t-1} across the entire portfolios.

While we know that the First principal component captures the most amount of variability in the time series of stocks returns, we do not know how the weights (loadings) this component assigns to each stock vary through time. In order to explore the extent of each stock weight change in each principal component (PC) from one year to another. At the end of each year, we sum the square of the difference in each security's weights in each principal component.

$$S = \sum_{i=1}^{n} \left(W_i(t) - W_i(t-1) \right)^2$$
(3.1)

Where $W_i(t)$ is the weight of the security i at time t for the same PC, while n: is the total number of stocks. Table (3.1) shows this change statistics. The change is much more apparent in PC 2, 3, 4 and 5 in comparison to PC1. The mean shows that amount of change in PC 2, 3, 4 and 5 is almost five times higher than PC 1. This indicates that PC 2, 3, 4 captures more dynamic characteristics in the data. Any portfolios containing PC 2, 3, 4 or 5 will need to be rebalanced more frequently than on annual basis to reflect the true securities weights of these components. This is one of the main reasons why we perform our PCA on annual and semi-annual basis.

Figure (3.1) and (3.2) show PC1, PC2, PC3, PC4 and PC5 weights distribution over the period 1927 to 2015. We see that the min and max range is large up to 1970 relative to the range afterwards, and it decreases as we approach the present. The same applies to the first and second quartiles statistics. The effect of having an upper and lower weight constraint at 0.1 and -0.1 respectively is apparent during that period which is obvious from the point on plotted on both values. Weights outside the permissible range of (-0.1,0.1) seems to decrease as the number of firms increases as we approaches the present.

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Figure 3.1: PC1 weights distribution

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Figure 3.2: PC2, PC3, PC4 and PC5 weights distribution

3.1.2 Principal Portfolios Analysis

Regression

We run the four factor regression model,

$$R_{it} = \alpha_i + \beta_{Mi}(R_{Mt} - R_{Ft}) + \beta_{smb.t}SMB_t + \beta_{hml.t}HML_t + \beta_{mom.t}MOM_t + e_{it}$$
(3.2)

In this equation R_{it} is the return on Principal portfolio i or composite portfolio for period t, RF_t is the risk-free return, R_{Mt} is the return on the value-weighted (VW) market portfolio, SMB_t is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks, HML_t is the difference between the returns on diversified portfolios of high and low B/M stocks, MOM_t is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios and e_{it} is a zero-mean residual. Treating the parameters in (3.2) as true values rather than estimates, if the factor exposures β_{Mi} , $\beta_{smb.t}$, $\beta_{hml.t}$ and $\beta_{mom.t}$ capture all variation in expected returns, the intercept α_i is zero for all securities and portfolios i.

In the time-series regressions, the slopes and R' values are direct evidence on whether different risk factors capture common variation in portfolios' returns.

• First principal component PC1:

The first principal component seems to capture much of the information about crosssectional variation in average stock returns. Table (3.2) shows that with a volatility of 22.39, its average return is 7.25% for the annual rebalancing PC1. Its Sharpe ratio 0.32 which is slightly less than the market (0.39). What is peculiar about the PC1 is its regression statistics. When regressing its return against the four factor model: Market, SMB, HML, and momentum, we find that that R² is very high 0.76. It can explain up 76 percent of the variation in the model. Its market beta is 96 %(t_{val}=47.3) which indicates that it moves almost as much as the market and with the same direction. While its momentum beta β_{MOM} is not statistically significant, it has positive exposure to the small companies $\beta_{SMB}=44.5\%(t_{val}=13.9)$ and a negative exposure to value stocks with a $\beta_{HML}=-24.4\%$ (t_{val}=-7.9) which is suggesting that the PC1 has more exposure to growth and small stocks. Alpha is not statistically significant.

The semi-annual rebalanced PC1 has a very close regression statistics, except for the momentum $\beta_{mom,t} = 11.5(t_{val} = 5.0)$, which has a positive exposure to momentum.

The short side of the first principal component is negligible throughout the 88 years period since the number of companies in it is either zero or very small number that why the 1st PC is predominately long. Since these results are out-of-sample the first PC characteristics are one of the most useful one.

• Second principal component PC2:

Table (3.3) shows that annual PC2 is the most promising principal component as an investment strategy by itself or as a member of composite portfolios. Its annual average returns 13.44 % are considerably higher than the PC1 ones for the same extent of volatility 22.33 %. It has a Sharpe ratio of 0.60 which is higher by about 50 and 55 % than the market and PC1 Sharpe ratio respectively. PC2 regression statistics are different than PC1, The four factor model can only explain up to 15 % of PC2 annual and semi-annual returns behaviour as $R^2=0.15$. It has small positive statistically significant exposure to SMB of $\beta_{smb.t} = 14.7(t_{val} = 2.5)$, its market beta is half the PC1 beta $\beta_{Mi} = 44.1(t_{val} = 11.7)$ i.e. it moves in the same direction as the market but to a less extent which is a very attractive feature in times of market turbulence. While It has small positive exposure to the momentum factor a $\beta_{mom.t} = 8.8(t_{val} = 2.0)$, its exposure to HML is not statistically significant. It has positive and statistically significant alpha of $0.7\%(t_{val} = 3.8)$ which indicates that some of its out-performance cannot be explained by the four factor model.

While the semi-annual Sharpe ratio for PC2 of 0.57 is not far from the annual one of 0.60, it regression statistics are not the same. \mathbb{R}^2 drops to 0.11 and It exposure to both SMB and MOM is not statistically significant at the 0.05 level. Only the exposure to Market and HML factor are significant. It has a positive exposure Market beta of 37.4 % ($t_{val} = 9.6$) and $\beta_{hml.t} = 12.3(t_{val} = 2.1)$. It still keep a positive alpha of 0.7%($t_{val} = 3.8$) which is statistically significant and different from zero. The four factor regression model can not explain much of second principal portfolio returns variation.

The total side regression statistics, as table (3.3), are determined by the long and short sides of PC2. While both the of the semi-annual and annual long side regression statistics have exposure to Market, SMB and momentum, we see that the short side has negative exposure to these and a positive one to the HML factor. The capacity of the semi-annual PC2 to produce a Sharpe ratio of 0.57 with having exposure to only market and HML is quite significant since firms has not been sorted based on value factor or any firm specific fundamental characteristics (B/E, B/M, etc.) but rather based the PCA mathematical model. In addition to that having strategy that have almost 50 % better Sharpe ratio than market with market beta of 37% and having only HML exposure as statistically significant make it quite an attractive strategy for diversification purposes in portfolio construction.

• Third principal component PC3:

Table (3.3) shows that the third principal component annual average returns and Sharpe ratio are 8.9 % and 0.40 respectively. Its R² drops a little bit further to 0.08. It has a negative exposure to size factor β_{SMB} =-24.5%(t_{val}=-3.9) i.e. its returns are positively affected by the large firms. While its exposure to both value and momentum are not statistically significant, It has some exposure to market with a β_{Mi} = 33.7(t_{val} = 8.6) and a positive and statistically significant alpha of 0.6%(t_{val}=-3.0).

The semi-annual PC3 is different than the annual one in some of these statistics,

its alpha is not statistically significant and it has a lower Sharpe ratio of 0.31 and slightly higher \mathbb{R}^2 of 0.10. Also it has a positive exposure to size factor $\beta_{smb.t} = 17.2\%(t_{val} = 2.8)$, i.e. its performance is more affected by small size firms. It has a positive statistically significant exposure to momentum factor $\beta_{mom.t} = 10.6\%(t_{val} = 2.3)$.

By examining the long and short sides regression statistics we get a better understanding of the total side statistics. One of the most important measures to notice is that the volatility of the long and short sides of most components is much higher than that of the total sides. The long side of annual PC3 has a Sharpe ratio of 0.38 and has big exposure to market and SMB with their betas 191% and 78 % respectively. While its exposure to momentum is not statistically significant, it has big negative exposure to the HML factor. The short side has a big negative exposure to market and SMB causing the overall exposure to be net negative for the total side.

The annual PC3 uniqueness lies in that it can achieve a Sharpe ratio as good as the market but with negative exposure to the SMB factor, a relatively small market beta and with other factor not statistically significant.

• Fourth principal component PC4:

Table (3.3) shows that PC4 has average returns of 8.12% and a Sharpe ratio of 0.36. Its alpha and exposure to value factor is not statistically significant. It has a positive market beta of $32.9\%(t_{val}=8.4)$, a positive exposure to small firms returns $\beta_{smb} = 16.7(t_{val} = 2.7)$ and also positive exposure to momentum factor $\beta_{mom} = 16.7(t_{val} = 2.0)$. We also notice again the continued pattern of low R² of 0.09. The semi-annual PC4 has slightly different values, only the Market and size factors are statistically significant. With $\beta_M = 38.5\%(t_{val} = 10)$ and $\beta_{smb} = 15.3\%(t_{val} = 2.5)$.

• Fifth Principal Component PC5

Table (3.3) shows that PC5 has the second largest Sharpe ratio of the five annual principal components 0.49 with an average annual return of 11.0. All factors are statistically significant, while it has a positive exposure to market factor, The market beta $\beta_M=32.8\%(t_{val}=8.3)$, it has more to exposure to big firms $\beta_M=-14.6$ %($t_{val}=-2.3$). Its exposure to both value and momentum is positive with $\beta_{HML}=13.2$ %($t_{val}=2.2$) i.e. growth stocks do not influence its returns. $\beta_{MOM}=11.4$ %($t_{val}=2.5$). It has a statistically significant positive alpha of 0.6 % ($t_{val}=3.1$). So far we have seen only three annual components have a statistically significant and positive alpha: PC2, PC3 and PC5.

The semi-annual PC5 has only two significant factors: the market and size, with a positive $\beta_M=32.8\%(t_{val}=8.3)$ and positive exposure to size factor $\beta_{smb}=15.3\%$ ($t_{val}=2.4$). Its alpha is not statistically significant. While the semi-annual total side Sharpe ratio is relatively small, half the market Sharpe ratio, the long side of the semi-annual Sharpe ratio is almost as good as the market with volatility three times as the market one.

Having a higher than the market Sharpe ratio, statistically significant four factors with negative exposure to SMB and low market beta distinguish PC5 and make it a good candidate for building diversified portfolios.



Figure 3.3: Single annual and semi-annual PC's four factor model exposure summary. White rectangles represent exposures that are not significant at 0.05. mkt-b: market beta, SMB-B: size factor beta, HML-B: value factor beta, MOM-B: momentum factor beta. a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC

Overall, For the total side, as table (3.3) shows, all components have exposure to the market, this exposure is the highest for PC1 and decreases to the lowest for PC5, and is statistically significant for all. PC1 has exposure to the SMB factor for both semi-annual and annual components. While PC3 and PC5 annual portfolios returns have exposure to big firms, it is the opposite for semi-annual i.e. their returns are influenced by the small firms returns. Exposure to the momentum factor is different for the annual and the semi-annual portfolios for the same component. Apart from the total sides, we have calculated the regression coefficients for the Long (LO) and short(SH) side for each components and this will give us insights into the portfolios composed from single components, this allow us to do in-depth analysis, draw conclusion about these different side for the same components and get valuable insights about their uniqueness. What really makes them important is their Sharpe ratio, their distinct exposure to different factors and low correlation.

Panel A:	Annual				Regress	sion: PC	\sim Market	+ SMB $+$	HML + 1	MOM
Component	Side	Average Ret%	Volatility %	Sharpe Ratio	\mathbb{R}^2	α (t_val)	$egin{aligned} & eta_{Mkt} \ (ext{t_val}) \end{aligned}$	β_{SMB} (t_val)	β_{HML} (t_val)	β_{MOM} (t_val)
PC1	тот	7.25	22.39	0.32	0.76	0.0	96.0	44.5	-24.4	4.2
	LO	7.27	22.4	0.33	0.76	(-0.3)	(47.3) 96.1	(13.9) 44.5	(- 7.9) -24.4	(1.8) 4.2
						(-0.2)	(47.4)	(13.9)	(-7.9)	(1.8)
	SH	- 0.02	0.11	-0.20	0.04	0.0	-0.1	(-1.4)	0.0	0.0
PC2	тот	13.44	22.33	0.60	0.15	0.7	44.1	14.7	7.0	8.8
		10.01	20.42	0.49	0 59	(3.8)	(11.7)	(2.5)	(1.2)	(2.0)
	LO	19.01	39.43	0.48	0.58	(2.1)	(31.5)	(10.3)	(-5.7)	(4.1)
	SH	- 5.56	29.72	- 0.19	0.53	0.2	-104.2	-62.0	47.9	-13.9
PC3	тот	8 90	22 32	0.40	0.08	(1.2)	(-27.8)	(-10.5)	(8.4)	(- 3.2)
105	101	0.00	22.02	0.40	0.00	(3.0)	(8.6)	(-3.9)	(0.4)	(- 0.5)
	LO	17.92	47.46	0.38	0.64	0.3	191.2	78.0	-62.2	9.4
	SH	- 9.02	42.46	- 0.21	0.62	(1.2)	(36.6) -157.5	(9.4)	(- 7.8) 64.5	(1.6)
	511	0.02	12.10	0.21	0.02	(1.2)	(-32.9)	(-13.5)	(8.8)	(- 2.1)
PC4	тот	8.12	22.27	0.36	0.09	0.4	32.9	16.7	3.2	9.2
	LO	20.62	56.18	0.37	0.71	0.3	(8.4) 229.6	(2.7) 120.4	-76.3	6.3
					0.1.2	(1.0)	(41.5)	(13.8)	(- 9.1)	(1.0)
	SH	-12.49	50.1	-0.25	0.67	0.1	-196.7	-103.7	79.5	2.9
PC5	тот	10.99	22.35	0.49	0.07	0.6	(-37.1) 32.8	-14.6	(3.8)	(0.3)
						(3.1)	(8.3)	(- 2.3)	(2.2)	(2.5)
	LO	25.43	59.72	0.43	0.71	0.4 (1.4)	247.7 (41.8)	(12.5)	-57.1	(2.5)
	SH	-14.42	55.34	- 0.26	0.68	0.2	-214.9	-132.2	70.4	- 5.6
						(0.7)	(-37.4)	(-14.5)	(8.0)	(- 0.8)
Panel B:	Semi-Annual									
PC1	тот	7.62	22.36	0.34	0.77	-0.1	97.3	46.2	-18.9	11.5
	IO	7 62	99 A	0.34	0.77	(-0.8)	(49.2) 97.5	(14.7)	(- 6.2)	(5.0)
	LO	1.02	22.4	0.54	0.11	(-0.8)	(49.2)	(14.7)	(- 6.2)	(5.0)
	SH	-0.01	0.16	-0.07	0.07	0.0	- 0.2	- 0.1	0.0	- 0.1
PC2	тот	12.79	22.39	0.57	0.11	(0.9)	(- 7.3)	(- 2.0)	(- 0.2)	(- 3.4)
					0.22	(3.8)	(9.6)	(0.5)	(2.1)	(1.3)
	LO	18.24	41.62	0.44	0.59	0.4	160.8	72.5	-47.4	19.8
	SH	-5.45	34.42	-0.16	0.55	0.3	(32.9) -123.4	-69.6	(-0.4) 59.8	-13.8
D.C.				0.01	0.1	(1.5)	(-29.0)	(-10.4)	(9.2)	(- 2.8)
PC3	тот	6.96	22.39	0.31	0.1	(1.1)	33.8 (8.6)	(2.8)	9.2 (1.5)	10.6 (2.3)
	LO	19.91	52.3	0.38	0.70	0.1	212.6	117.6	-47.8	23.2
		10.04	45 19	0.00	0.69	(0.4)	(40.6)	(14.2)	(-6.0)	(3.8)
	SH	-12.94	45.13	-0.29	0.68	(0.1)	(-37.8)	(-13.4)	(7.9)	-12.6
PC4	тот	7.72	22.33	0.35	0.12	0.3	38.5	15.3	5.2	7.9
	τo	24.20	63 4	0.38	0.76	(1.5)	(10.0)	(2.5)	(0.9)	(1.8)
	LO	24.29	05.4	0.58	0.70	(0.4)	(47.2)	(16.2)	(-7.2)	(3.7)
	SH	-16.57	56.93	-0.29	0.7	0.2	-229.8	-130.7	67.3	-16.8
PC5	тот	4.84	22.36	0.21	0.08	(0.7)	(-40.4)	(-14.5) 15.3	(7.8)	(- 2.5) 6.8
100	101	1.04	22.00	0.21	0.00	(0.6)	(7.8)	(2.4)	(0)	(1.5)
	LO	26.17	66.58	0.39	0.76	0.1	278.7	159.4	-54.9	27.8
	SH	-21.35	60.47	-0.35	0.73	(0.4) 0.0	(46.4) -247.8	(16.8)-144.1	(-6.0) 55.1	(4.0)-21.0
						(0.0)	(-43.2)	(-15.9)	(6.3)	(- 3.2)

 Table 3.2:
 Principal components Annual Performance statistics, TOT: stands for total side (includes positive and negative weights), LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

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\mathbf{pc}	Rebalancing Frequency	Average of annual corelation	Standard deviation of annual correlation
1	12	0.93	0.07
	6	0.92	0.07
2	12	0.42	0.36
	6	0.34	0.37
3	12	0.28	0.38
	6	0.30	0.34
4	12	0.28	0.46
	6	0.29	0.33
5	12	0.24	0.36
	6	0.24	0.37

Single Strategies Accumulation Graphs and Correlation

Table 3.3: Principal components annual correlation mean and standard deviation. We calculate annual correlation for first five annual and semi-annual principal components over the period 1927-2015.

Figure (3.5) and (3.6) shows the accumulation graphs for the total side for the first five components on annual and semi-annual basis. These graphs contain a wealth of information about these components characteristics. First of all, the correlation between PC1 and the market is very high as also shown in table (3.3) the mean and median of annual correlation is over 90%. By performing PCA we can obtain a component that will have over 90 % correlation and a β_{Mkt} =98% out-of-sample, and this correlation does vary over time, as the curve in (3.4) shows, it remains high over the entire 89 years.

Many individual investors and professionals investing in the stock market use the correlation with the market in many different ways. Figure (3.5) and (3.6) show that Over the last 88 years, PC1 had a high correlation with market. It also shows that the semi-annual PC1 outperformed both the market and annual PC1 up to 1990 when the market performance was higher mainly due to rise of the micro and small caps during to the internet bubble. The end accumulation value for the market was higher than both semi-annual and annual PC1.

Probably the second most striking feature to notice in Figure (3.5) and (3.6) is PC2 Path and accumulation value. PC2 beats the market almost during the entire period except a period of about 5 years from 1942 to 1950. PC2 path is much more attractive in terms riskreward than the market and all other principal portfolios with a Sharpe ratio of 0.60 and 0.57 for the annual and semi-annual components respectively. Its final accumulation value is five times as much as the market. Its mean correlation is 42 % (annual)and 34 % (semi-annual). PC2 annual correlation can vary substantially and even have negative correlation with the market, for example the correlation was -0.55, 0.49, 0.09, 0.30, -0.35 and 0.27 in 2012, 2008, 2002, 2001, 1991 and 1987 respectively. A similar pattern can be noticed for the semi-annual PC2.

As we go further from PC1, the correlation with the market decreases. PC3 has low correlation with the market: (mean = 28% and standard deviation = 0.38). Its accumulated

value is higher than the market for the annual component. Figure (3.6) shows that PC4 annual component accumulation curve is more attractive than the semi-annual one and even than the market if we exclude the recent recession. Annual PC4 annual correlation with the market has:(mean= 0.28 and standard deviation=0.46).

Annual PC5 is the second best annual component in terms of risk-reward ratio with a Sharpe ratio of 0.49. Its final accumulation is more than five times the market one. One the most noticeable patterns of PC5 annual portfolio is its strong negative correlation with the market during last three big recessions with correlation: -0.40, -0.01, -0.45 and -0.55 in 2008, 2001 and 1973 respectively. On average it has one of the lowest correlations with the market (mean=0.24, standard deviation=0.36).



Figure 3.4: Annual correlation with the market curves, top five are annual components and bottom five are semi-annual components

The most important aspect for these components that they have low correlation between themselves and with the market and their distinct exposure to the factors in the regression.



Figure 3.5: PC1, PC2 and PC3 Accumulation Curve



Figure 3.6: PC4 and PC5 Accumulation Curve

3.2 Composite Portfolios Candidates

The previous analysis has highlighted many characteristics for the first five components and their three sides. The first principal component has a stable high correlation with the market out-of-sample and a low correlation with the remaining four components. Few components and sides have a Sharpe ratio equal or higher than the market. Consequently, it is natural to expect that combining multiple sides from these remaining components with these characteristics have good chance to result in portfolios with attractive risk-adjusted returns. We investigate:

- Whether certain combinations of these strategies can consistently generate better than the market risk-adjusted returns.
- If there are certain strategies which frequently appear in these portfolios
- Whether these components short sides can play a role in optimizing these portfolios risk-adjusted returns within long-short portfolios.
- What characteristics these portfolios have (Exposure to four factors, accumulation value, volatility, drawdowns, robustness to transaction costs, securities weights distributions, exposure to industry sectors during recessions).

To answer these questions we construct portfolios according to (2.4). Table (3.5b) shows that the exposure characteristics of long strategies candidates to (MKT, SMB and MOM), make the short sides candidates good strategies to reduce or neutralize composite portfolios extreme exposures to the stated factors. This is especially apparent when we use the long sides of any of the components in composite portfolios construction since these have large exposure to (MKT, SMB and MOM).

\mathbf{PC}	Side	Rebancing	$\mathrm{freq}\%$
2	Total	annual	48.6
2	Total	semi-annual	43.7
2	Long	annual	39.9
5	Total	annual	39.7
4	Short	annual	33.3
3	Short	annual	32.8
5	Short	annual	30.9
2	Short	semi-annual	30.7
5	Long	annual	29.5
2	Long	semi-annual	29
4	Short	semi-annual	28
4	Total	annual	25.8
5	Long	semi-annual	25.6
3	Total	annual	25.2
2	Short	annual	23.6
3	Short	semi-annual	23.5
4	Long	semi-annual	20.4
3	Long	semi-annual	19.3
5	neg-SH	semi-annual	17.9
3	Long	annual	16.7
4	Long	annual	15.9

Table 3.4: Strategies frequency(%), out of there are have 1653 composite portfolios each have 0.65 Sharpe ratio

We put the resultant composite portfolio in a decreasing order in terms of their Sharpe ratio. Table (3.6) show three composite portfolios with highest Sharpest ratio. Not surprisingly, we see the strategies with the highest Sharpe ratio and lowest correlation dominating the best performing portfolios.

m6 p5SH-

Annual Sharpe Ratio	Component	Side	Rebalancing Frequency
	Long car	ndidates	
0.60	PC2	TOT	12
0.49	PC5	TOT	12
0.48	PC2	LO	12
0.43	PC5	LO	12
0.40	PC3	TOT	12
0.38	PC3	LO	12
0.37	PC4	LO	12
0.36	PC4	TOT	12
0.57	PC2	TOT	6
0.44	PC2	LO	6
0.39	PC5	LO	6
0.38	PC4	LO	6
0.38	PC3	LO	6
0.31	PC3	TOT	6
0.21	PC5	TOT	6
	Short car	ndidates	
-0.19	PC2	$_{\rm SH}$	12
-0.21	PC3	$_{\rm SH}$	12
-0.25	PC4	$_{\rm SH}$	12
-0.26	PC5	$_{\rm SH}$	12
-0.16	PC2	$_{\rm SH}$	6
-0.29	PC3	$_{\rm SH}$	6
-0.29	PC4	$_{\rm SH}$	6
-0.35	PC5	$_{\rm SH}$	6

m6_p4SH m6_p3SHm6_p2SHa_p5SHa p4SHa_p3SHa p2SH-Beta m6_p5LO m6_p4LO -200 m6_p3LO -Strategy 100 m6_p2LO a p5LO-0 a_p4LO--100 a_p3LO--200 a_p2LOm6_p5TOT m6_p4TOT m6_p3TOT m6_p2TOT a_p5TOT a_p4TOT a_p3TOT a_p2TOT mkt_b SMB_B HML_B MOM_B Factor

(b) The exposure summary of the long and

short side candidates to the four factor model

a: stands for annual components, m6: for

Blue: positive exposure, Red:

semi-annual ones.

negative Exposure

(a) Long and short sides

candidates and their Sharpe ratio.

Table 3.5: Composite portfolios candidates



Figure 3.7: The cross correlation among our thirty strategies. a_- : stands for annual components, m6₋:semi-annual components, ToT: total side (includes positive and negative weights), LO: Long side (includes only positive weights), SH: short side (includes negative weights).

We notice that total sides (the top-left 10x10 square) have quite a low correlation among each other. All long sides have high correlation with PC1. Total and long side have low cross-correlation among each other which is slightly higher than the average correlation among total sides. All short sides have high negative correlation with the PC1 and consequently with the market.

3.2.1 Composite Portfolios Annual Returns Parameters

Portfolio	1st	2nd	3rd	4th	5th	6th
Portfolio1	a-p3SH	a-p4SH	a-p2TOT	a-p5TOT	m6-p2LO	m6-p4LO
Portfolio2	a-p2SH	a-p4SH	a-p2LO	a-p5TOT	m6-p2TOT	m6-p3LO
Portfolio3	m6-p4SH	a-p4SH	a-p2TOT	a-p5TOT	a-p3LO	m6-p5LO

Table 3.6: Top three composite portfolios

Component	Average Ret (%)	Volatility (%)	Annual Sharpe Ratio	Accumulation Value 1928-2015	Maximum Drawdown
Port1	7.6	9.6	0.79	513.3	0.25
Port2	7.4	9.5	0.78	459.0	0.27
Port3	7.4	9.9	0.75	424.0	0.27
Market	7.6	18.77	0.40	157.6	0.84

Table 3.7: Top three composite portfolios annual performance statistics

Table (3.7) shows some of the attractive features of the composite portfolio. First of all, we notice they have a Sharpe ratio which almost twice as much as the market, this is mainly not due to producing substantially higher return but due to producing a similar returns to the market but with less than half its volatility. Even though it has half the volatility of the market, we see they still can beat the market, their accumulation value is twice as much the market mostly and with the minimum is at least 50% higher than the market. Their maximum drawdown is about 0.25-0.27 in comparison to the market (0.80).

The Accumulation graphs in figure (3.8) shows that while it is impossible to completely avoid all of the declines of the stock market, excluding the first principal component dimension which is basically the market and focusing on the remaining four components offer a smoother path to generating sustainable persistent returns.

We have seen in figure (3.5) PC1 has very high correlation with the market, and it captures most of the highs and lows of the stocks market to a large extent. This is not the case for the composite portfolios, figure (3.8) shows that these portfolios were very resilient to the big drawdowns that the US stock market suffered from in the largest four recessions 1929, 1973, 2000 and 2008, they have much shorter recovery period in comparison to the market. The market accumulation value curve shows that it might take up to 15 years to recover the losses it incurred during recession, which is disastrous for pensioners and retires. The only period where we see that these composite portfolios accumulation value curves are not very attractive from 1986 to 1996 in comparison to the market, which was in part fuelled by internet start-ups in the second half of this period. This is due to removing micro-caps from our data sets. At the same time these composite portfolios passed through the 1987 and 1991 gulf war without a major decline in contrast to the market.



Accumulation Graphs

Figure 3.8: The accumulation graph of the top three composite portfolios

Figure (3.9) shows the composite portfolios performance relative to the market. These composite portfolios relative value has been above market for the entire period, it also shows that their relative value experience sharp increase during recessions and distress periods. The relative value decreased at rapid rate during the nineties due to the increase value of the market fuelled by the micro-caps and IPOs of the internet firms which are excluded from our dataset.



Figure 3.9: The relative performance graph of the three composite portfolios in comparison to the market

3.2.2 Regression

Four Factor

We run four factor model regression,

$$R_{it} = \alpha_i + \beta_{Mi}(R_{Mt} - R_{Ft}) + \beta_{smb.t}SMB_t + \beta_{hml.t}HML_t + \beta_{mom.t}MOM_t + e_{it}$$
(3.3)

In this equation R_{it} is the return on composite portfolio i for period t, other variable are defined in equation equation (3.2). Parameters here are true values rather than estimates, if the factor exposures β_{Mi} , $\beta_{smb.t}$, $\beta_{hml.t}$ and $\beta_{mom.t}$ capture all variation in expected returns, the intercept α_i is zero for portfolio i.

Table (3.8) Shows the regression statistics. First of all, the R-squared is quite low and ranges between 0.20 and 0.27 and alpha is statistically significant and not zero in all portfolios. These two parameters indicate that the four factor model can only explain up to 25% of the variation in this portfolios returns. Alpha positivity and its t-value size of minimum of 4.7 over a period eighty eight years periods shows that these portfolios has persistent excess returns in comparison to the four factor model. All other factors are statistically significant except the SMB factor. All portfolios have a positive exposure to the market which ranges from (21 to 26)%, which is particularly attractive during distress period.

Portfolio	\mathbb{R}^2	$lpha ({ m t}_{val})$	$\begin{array}{c} \text{Market-}\beta \\ (\mathbf{t}_{val}) \end{array}$	$\frac{\text{SMB-}\beta}{(t_{val})}$	$\begin{array}{c} \text{HML-}\beta \\ (\text{t}_{val}) \end{array}$	$\begin{array}{c} \text{Mom-}\beta\\ (\mathbf{t}_{val}) \end{array}$
Port1	0.25	0.37 (4.8)	25.0 (16.6)	2.1 (0.85)	9.0 (3.9)	9.0 (5.3)
		()	(_0.0)	(0.00)	(010)	(010)
Port2	0.20	0.38	21.7	2.8	11.0	9.0
		(4.8)	(13.9)	(1.14)	(4.5)	(4.8)
Port3	0.27	0.36	26.7	3.7	8.0	7.0
		(4.6)	(17.3)	(1.5)	(3.5)	(3.9)

 Table 3.8:
 Regression statistics for top three composite portfolios

Combining these market exposures with having a Sharpe ratio twice as the market make these composite portfolios deserving of further examination. "The negative correlation between value and momentum strategies and their high positive expected returns implies that a simple combination of the two is much closer to the efficient frontier than either strategy alone, and exhibits less variation across markets and over time." Asness et al. (2013). Both HML and momentum exposures are positive and statistically significant, which indicate that these portfolios returns are more affected to a small extent with value firms with momentum.

Betting Against Beta Regression

Betting against beta (BAB) is another factor which attracted attention recently, "Because constrained investors bid up high-beta assets, high beta is associated with low alpha, as we find empirically for US equities, 20 international equity markets, Treasury bonds, corporate bonds and futures. A betting against beta (BAB) factor, which is long leveraged low-beta assets and short high-beta assets, produces significant positive risk-adjusted returns." Frazz-ini and Pedersen (2014)(Frazzini and Pedersen (2014)). Since all our composite portfolios have relatively low beta, we will run regression to check if their return can be explained by BAB model.

$$R_{it} = \alpha_i + \beta_{BAB}(R_{BAB}) + e_{it} \tag{3.4}$$

Where R_{it} , is the composite portfolio monthly returns, R_{BAB} , is monthly self-financing excess returns of long/short equity Betting against Beta (BAB) factors. If the factor exposure β_{BAB} captures all variations in expected returns, the intercept α_i should be zero for portfolio i and R² relatively High. BAB model USA equity monthly returns over a period (1931-present) are provided by AQR hedge fund.¹.

¹https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Monthly

Portfolio	PORT1	PORT2	PORT3	Market
\mathbf{R}^2	0.004	0.005	0.008	0.009
lpha%	0.40	0.40	0.30	0.30
t-val	3.45	3.22	2.51	1.32
$\beta\%$	9.00	10.00	14.00	16.00
t-val	1.92	2.18	2.87	1.76
Table 2.0	. Dom	agion ato	tistics of	Detting

Table 3.9:Regression statistics of Betting
against Beta factor

Regression statistics in Table (3.9) shows that R^2 is very low ranges between (0.004 to 0.009) and α and alpha is not zero, it is positive and statistically significant. Which however only two composite has a statistically significant positive exposure to BAB factor with a small beta ranges from 9 to 14 %. This indicates that while our composite portfolios have low beta, Betting against Beta model can not explain the composite portfolios returns variation.



3.2.3 Weights Time series Analysis

Figure 3.10: Shows first composite portfolio Port1 weights time series. Blue bars: when the mean is greater the median, otherwise red

Port1 weight time series analysis shows that weights distribution changes dramatically as time passes. Initially, as figure (3.10) Shows, we notice few consecutive blue bars at the beginning of the time series up to December of 1934 which indicates a distribution that is skewed to the right i.e. large positive weights predominates, then the red colours bars take over i.e. the sum of small weights become larger. Also we notice that the min-max ranges changes dramatically as we approach the present. This range is large in the first half of the time series with the minimum weight could be as small as (-3.75%) and maximum value

could be as large as (3.75%), this range become smaller and smaller at last quarter of the time series as we can see the min is often less than -0.5% and the Max is less than 0.75%. This partly driven by the change in the number of publicly traded stocks in the market, as there were fewer firms traded on the stock exchange in the early days, but this number increased substantially to reach 4381 at 31-12-2015. This is also one of the reasons that help composite portfolios avoiding big drawdowns as no stock could have a major impact on the portfolio performance.



3.2.4 Maximum Drawdown

Figure 3.11: Drawdowns curves for the market and three composite portfolios over period 1928-2015

From	Trough	То	Depth	Length
1929-09	1932-06	1945-02	-0.85	188
1968-12	1974-09	1983-04	-0.56	173
2000-04	2009-02	2013-01	-0.54	154
1987-10	1987 - 11	1991-05	-0.31	45

Table 3.10: Market drawdowns statistics

Maximum Drawdown is a statistics that gives an indication about strategies capacity to preserve capital and how quickly it recovers losses. Capital preservation is one of the most important issues to investors. The MDD measures the largest High-to-trough decline in the accumulation value of a portfolio (before a new High is reached). Table (3.10) shows the market portfolio largest four drawdowns. The biggest drawdown (-0.85) was in the great depression, it took the market 15 years to recover the losses, the second largest drawdown



Figure 3.12: The market fifty worst monthly returns and corresponding monthly returns for top three composite portfolios

(-0.56) was from 1968-to-1983, as the figure shows its length was almost 14 years, the third largest was of similar magnitude and its length was 12 years. This third drawdown included two severe recession, the dotcom bubble and the recent financial and banks crises, there were two huge declines of at least (-0.45%), that is why it is called double dip recession as also shown in Figure (3.11).

So examining the composite principal portfolios shows that by excluding the first principal portfolios and investing in the remaining components we get portfolios that have much smaller drawdowns and suffer less during recessions Figure (3.11) shows. The composite portfolios drawdowns are substantially less than the market with a maximum drawdown of (-0.27). Another crucial characteristic to notice is the recovery period for composite portfolios is much shorter. Figure (3.13) panel (b) shows that the market outperform the composite portfolio in some periods, but since the composite portfolios have smaller drawdowns and shorter recovery period, they always result in higher accumulation value and better performance in terms of risk adjusted returns. In order to further put composite portfolios returns under the spot light, we look at worst fifty monthly market returns since 1927 in order to compare them to the composite portfolios returns with the same date. Figure (3.12) shows that the composite portfolios decline much less than the market in these times and in some occasions even rise as well.

The total low overall volatility that these composite portfolios enjoy is such an attractive feature especially when they are able to produce better than market returns. But how does these portfolios volatility look like on an annual basis? Is their volatility highly correlated with the markets during recessions? Figure (3.13) panel (a) shows the curve of the annual volatility time series. The graph shows these portfolios volatility is consistently low during the 88 years. While it rises during distress periods when the markets are volatile, the



volatility even with increase is still less than half the market volatility. These portfolios persistent low volatility and resilience to shocks during recessions and bubbles burst further increase their favourability.

Figure 3.13: Annual returns and volatility time series for the top 3 portfolios

3.2.5 Portfolios Industry Composition During Recessions

Year	Sector			Bottom	5				Top 5		
200806	category	Banks	Fin	Rtail	Trans	Chips	Mach	Whlsl	Chems	Util	Oil
	weight	-0.11	-0.08	-0.05	-0.03	-0.02	0.03	0.03	0.03	0.12	0.20
	$\operatorname{Ret}(\%)$	-0.45	-0.59	-0.21	-0.24	-0.44	-0.50	-0.35	-0.47	-0.29	-0.33
200006	category	Softw	Chips	Telcm	ElcEq	Hardw	Insur	Util	Drugs	Fin	Banks
	weight	-0.08	-0.07	-0.02	-0.01	-0.01	0.03	0.03	0.05	0.06	0.06
	Ret	-0.50	-0.34	-0.40	-0.16	-0.27	0.41	0.51	0.37	0.16	0.22
198106	category	Oil	Coal	Agric	Mines	FabPr	Banks	BldMt	Util	Rtail	Fin
	weight	-0.28	-0.01	-0.01	-0.001	-0.001	0.04	0.05	0.05	0.05	0.07
	Ret	-0.21	-0.11	0.12	0.13	-0.06	0.11	-0.05	0.06	0.16	0.07
197306	category	Chips	Hshld	Whlsl	Drugs	Toys	Rtail	Util	Banks	Insur	Fin
	weight	-0.03	-0.02	-0.02	-0.02	-0.02	0.03	0.04	0.04	0.04	0.06
	Ret	-0.31	-0.25	-0.35	-0.13	-0.52	-0.36	-0.18	-0.13	-0.16	-0.26

Table 3.11: Composite portfolio 1 industry sectors weights Short Side: a-p3SH a-p4SH

Long Side: a-p2TOT m6-p2LO a-p5TOT m6-p4LO

where a_{-} : stands for annual components, $m6_{-}$: stands for semi-annual components

All the results shown so far indicates that these portfolios are consistently resilient to shocks and recessions and they have positive returns during distress period. Since on the aggregate level we know the main sectors that caused or were hit most in the past during different recessions, we examine these composite portfolios exposure to industry sectors during 4 of the worst recessions in financial market. We want to check these composite portfolios long and short exposure on a macro level. Table (3.11) shows the first composite portfolio Port1 Highest and lowest five industry exposure during: 1973, 1981, 2000 and 2008. We examine the dominant economic events, major government policies consequences in the period leading up to these recessions and calculate PC1 and Port1 industry exposures to check if there are any persistent similar patterns during these recessions.

Financial crises 2008: The latest crisis of 2008 is considered by many to have been the worst recession after the 1929 depression. It began in the mortgage market in the US and gradually pulled down the banks involved subprime mortgages business into it and gradually spread into the global financial markets. Many causes have been linked to this recession, as easy lending conditions, weak and fraudulent underwriting, deregulation, over-leveraging, incorrect pricing of risk and subprime lending.

Table (5.1) PC1 had relatively large positive exposure to Banks (0.055), Financials (0.069), Retails (0.051), Transport (0.022) and Electronic Equipment (0.05). Table (3.11) shows that Port1 had negative exposure (was short) to the five sector that hit most by the recession and was involved in activities led to the recession. Its highest short was in banks (-0.11), Financials (-0.08), Retails (-0.05), Transport (-0.03), Electronic Equipment (-0.02).

While this portfolio was overall long sectors like: Oil, Utilities, Wholesale, Machinery and Chemicals which also had negative returns during 2008, having substantial short exposure the sectors that were hit most helped to cap the drawdown and loss to a large extent.

The dot-com crash: this was another major recession that hit the US stock market. The initial monetization of the internet during the 1990s was one of the main reasons led to the increase of capital flow to the tech firms in the US. It was mainly start-up small firms that ignited the markets rise starting in the mid 90s'. Over-optimism, Easy credit, low interest rates, speculation, unrealistic growth projections, Unprecedented initial IPO's price rises and failing to not consider fundamentals in valuations and many other reasons.

"Because the amount of shorting is limited in practice, the pessimistic investors' beliefs got overwhelmed by the optimistic beliefs, leading to the high valuation of Internet stocks." (Ofek and Richardson, 2003).

All of this heated up Tech firms trading activities. Table (5.3) PC1 had substantial positive exposure to Software (0.13), Chips (0.07), Telecommunication (0.058), Electric Equipments (0.025) and hardware (0.029). Again we notice in Table (3.11) that the Port1 was overall short most major Tech sectors such as Software (-0.075), Chips (-0.065), Telecommunication (-0.02), Electric Equipments (-0.014) and hardware (-0.013).

1980/1981 Crisis: President Carter implemented expansionary fiscal and monetary policies to reduce unemployment, but a surge in inflation stopped this. Iranian revolution in January 1979 caused oil prices to increase and initiated the decade's second oil crisis.

" In 1980 inflation in the US rose to 15.2 percent. Government responses and policies propelled the economy into a downward spiral sending the housing and automobile industries into a decline." (Hogan, 2010).

Table (5.4) shows PC1 had a large positive exposure to Oil (0.122). Table (3.11) shows that Port1 had a huge short position (-0.28) in Oil sector, it was also short Coal (-0.01), Agriculture (-0.001) and Mines (-0.001) sectors. All of these sectors had negative returns in 1981, hence all these short positions were profitable and had substantial impact on the portfolio performance. At the same time Port1, as Table (3.11), was long Building materials (0.04), Banks (0.05), Utility (0.05), retails (0.05) and Financials (0.07), All of these long positions posted positive returns except for the Building material sector position.

Energy crisis 1973 Zarnowitz and Moore (1977) argue that many factors have contributed to the crisis:

(i) the highly stimulative monetary and fiscal policies of 1971 (in part) and 1972 (as a whole), which in turn were responding to the sluggish recovery and high unemployment rates of 1971; (ii) exogenous influences that led to steep rises in prices of food, oil and basic materials, including imports; (iii) the consequences of the depreciation of the dollar; (iv) the allocative distortions and "catch-up" effects of wage and price controls; and (v) the related increases in the attractiveness of export markets and shortages at home.

While the oil embargo imposed by the some of the Arab countries certainly played a role in the Oil crisis and substantial increase in prices, Zarnowitz and Moore (1977) assume that large amounts of commodities were purchased for storing rather than processing in production: "Speculation due to anticipations of price rises and, importantly, fears of inadequate supply raised the demand for raw materials by industrial users."

Table (5.5) shows PC1 had large positive exposure to Oil (0.09), Household (0.058), Electronic Equipment (0.056). Drugs (0.027), Wholesale (0.042) and Medical equipments (0.023). Table(3.11) shows that Port1 largest overall short were in Oil (-0.014), Drugs (-0.02), Household (-0.02), Chips (-0.03). Most of these sectors had negative returns except for Oil due the prices rise. Its largest overall long exposure were in Financials (0.066), Insurance (0.044), Banks (0.04), Utilities (0.036) and Retails (0.027) all of which had negative returns during 1973 due to the recession.

Overall, PC1 has high exposure to industry sectors that are hit most in recessions. By excluding PC1 from composite portfolios construction process, these portfolios have a low or in most cases negative exposures to these industry sectors, and consequently their drawdowns size are less than the market and PC1 during these recessions.

3.2.6 Transaction Costs

Trading in financial securities incur non-trivial costs. While estimating commissions, fees and taxes is feasible, implicit costs are often overlooked, quite difficult to calculate and their impact is underestimated. These implicit costs include but are not limited to: market impact, opportunity cost and market maker spread. Portfolios managers are in constant pursuit to outperform passive benchmarks, but often fail to do so due to many reason, one of the most contributing reason is the trading costs.

While these costs substantially reduce the profitability of trading strategies, implementing costs mitigation techniques can considerably reduce the transactions costs. To assess the impact of trading costs on the performance of our portfolios, we consider three hypothetical average trading costs (0, 0.5%, 1%). Different assets could have different costs, but we use the same value for all as an approximation.

Total Returns = Return from Stocks + return from cash - transaction cost

 Θ_t^i : is the number of shares at t.

 S_t^i : the price of asset i at t.

 r_t^0 : interest on cash at t.

 ε_i : transaction cost for asset i.

 $\Pi_t^i = \frac{\Theta_t^i S_t^i}{X_t^i}$: weight of asset i at time t (proportion of wealth in asset i)

 r_t^x : portfolio total net returns

 r_t^i : asset i gross returns

Total Returns = Return from Stocks + return from cash - transaction cost

$$\begin{split} X_{t} - X_{t-1} &= \Sigma_{i} \Theta_{t-1}^{i} (S_{t}^{i} - S_{t-1}^{i}) + (X_{t-1} - \Sigma_{i} \Theta_{t-1}^{i} S_{t-1}^{i}) \cdot r_{t-1}^{0} \cdot \delta t - \Sigma_{i} \varepsilon_{i} S_{t}^{i} |\Theta_{t}^{i} - \Theta_{t-1}^{i}| \\ \frac{X_{t} - X_{t-1}}{X_{t-1}} &= \Sigma_{i} \frac{\Theta_{t-1}^{i}}{X_{t-1}} (S_{t}^{i} - S_{t-1}^{i}) + \frac{(X_{t-1} - \Sigma_{i} \Theta_{t-1}^{i} S_{t-1}^{i})}{X_{t-1}} \cdot r_{t-1}^{0} \cdot \delta t + -\Sigma_{i} \varepsilon_{i} \frac{S_{t}^{i}}{X_{t-1}} |\Theta_{t}^{i} - \Theta_{t-1}^{i}| \\ \frac{X_{t} - X_{t-1}}{X_{t-1}} &= \Sigma_{i} \frac{S_{t-1}^{i} \Theta_{t-1}^{i}}{X_{t-1}} (\frac{S_{t}^{i} - S_{t-1}^{i}}{S_{t-1}^{i}}) + \frac{(X_{t-1} - \Sigma_{i} \Theta_{t-1}^{i} S_{t-1}^{i})}{X_{t-1}} \cdot r_{t-1}^{0} \cdot \delta t - \Sigma_{i} \varepsilon_{i} \frac{S_{t}^{i}}{X_{t-1}} |\Theta_{t}^{i} - \Theta_{t-1}^{i}| \\ &= \Sigma_{i} \Pi_{t-1}^{i} r_{t}^{i} + (1 - \Sigma \Pi_{t-1}^{i}) r_{t-1}^{0} \cdot \delta t - \Sigma_{i} \varepsilon_{i} \left| \Pi_{t}^{i} (1 + r_{t}^{x}) - \Pi_{t-1}^{i} (1 + r_{t}^{i}) \right| \\ &\Rightarrow 0 = \Sigma_{i} \Pi_{t-1}^{i} r_{t}^{i} + (1 - \Sigma \Pi_{t-1}^{i}) r_{t-1}^{0} \cdot \delta t - \Sigma_{i} \varepsilon_{i} \left| \Pi_{t}^{i} (1 + r_{t}^{x}) - \Pi_{t-1}^{i} (1 + r_{t}^{i}) \right| - r_{t}^{x} \end{split}$$

Table (3.12) shows that trading to keep the weight fixed for a six month and trading to rebalance every six month incur large transaction cost, composite portfolios Sharpe ratio drops to as low as 0.28.

In order to optimize the trading activity for these portfolios we use Gerhold, Guasoni, Muhle-Karbe, and Schachermayer (2014) appraoch. They introduce trading boundaries such that at each trading time interval (low/high frequency) they set an upper and a lower limit for each security in a portfolio. It is very simple technique where you only need initial weight (π), final weight (π_*), transaction costs (%) to calculate optimal trading weights. They use it for one risky asset. We add a constant "Factor" to account for the increase in the number of risky assets we trade. Gerhold et al. (2014) show that "It is optimal to keep the fraction of wealth held in the risky asset within the buy and sell boundaries".

NO Transaction Cost Eps=0			With 7 Eps:	0.01		
$\operatorname{Ret}\%$	Sh-R		$\operatorname{Ret}\%$	Sh-R	$\operatorname{Ret}\%$	Sh-R
7.6 7.4	0.79 0.78		$5.0 \\ 4.9$	$0.54 \\ 0.53$	2.7 2.6	0.29 0.28
7.4	0.75		5.3	0.54	3.1	0.32
		Optimal Tr	ading			
$\operatorname{Ret}\%$	Sh-R	Factor=	= 4 Ret%	Sh-R	Ret%	Sh-R
7.6	0.70		C F	0.71	5.0	0.62
7.4 7.4	0.79 0.78 0.75		6.4	0.71 0.70 0.69	5.9 5.7 6.0	0.63
	NO Tra Eps=0 Ret% 7.6 7.4 7.4 7.4 Ret% 7.6 7.4 7.4	NO Transaction Cost Eps=0 Cost Ret% Sh-R 7.6 0.79 7.4 0.75 Ret% Sh-R 7.6 0.79 7.4 0.75 7.6 0.79 7.4 0.75 7.6 0.79 7.6 0.79 7.4 0.75	NO Transaction Cost Eps=0 Image: Sh-R 7.6 0.79 7.4 0.78 7.4 0.75 Optimal Transactors Factors Ret% Sh-R Optimal Transactors Factors Ret% Sh-R 7.6 0.79 7.4 0.75	NO Transaction Cost With T Eps=0 Eps Ret% Sh-R Ret% 7.6 0.79 5.0 7.4 0.78 4.9 7.4 0.75 5.3 Optimal Trading Factor=4 Ret% Sh-R Ret% 7.6 0.79 6.5 7.6 0.79 6.5 7.6 0.79 7.6 0.79 6.5 7.4 0.78 6.4 7.4 0.75 6.7	With Transaction Cost With Transaction Cost Eps= 0.005 Ret% Sh-R Ret% Sh-R 7.6 0.79 5.0 0.54 7.4 0.78 4.9 0.53 7.4 0.75 5.3 0.54 Optimal Trading Factor=4 Ret% Sh-R Ret% Sh-R 7.6 0.79 6.5 0.71 7.4 0.79 6.5 0.71 7.4 0.78 6.4 0.70 7.4 0.75 6.7 0.69	With Transaction Cost Eps=0.005 Eps= Ret% Sh-R Ret% Sh-R Ret% 7.6 0.79 5.0 0.54 2.7 7.4 0.78 4.9 0.53 2.6 7.4 0.75 5.3 0.54 3.1 Factor=4 Ret% Sh-R Ret% 7.6 0.79 6.5 0.71 5.9 7.6 0.79 6.4 0.70 5.7 7.6 0.79 6.7 0.69 6.0

Table 3.12: Composite portfolios annual returns and Sharpe ratio statistics including transaction costs, Eps is transaction cost percentage value out of the total value of the transaction To achieve optimal trading returns with less transaction cost, we use this method which yields better returns, According to these steps:

(1) At each time step (t) we calculate the upper-limit and lower weight limit (π_{\pm}) for each security. Which is calculated according to optimal trading (buy/hold spread) Gerhold et al. (2014)

$$\pi_{\pm} = \pi_* \pm \left(\frac{3}{4\gamma} \pi_*^2 (1 - \pi_*)^2\right)^{1/3} (Factor) \varepsilon^{1/3} + O(\varepsilon^{4/3})$$
(3.5)

where:

 π_{\pm} : is the upper and lower weights boundary π_{*} : weight at time t Factor: is constant, the larger the Factor, the wider the range (π_{-}, π_{+})

 ε : transaction cost.

- (2) We compare each security weight at(t-1)to (π_{\pm}) and if:
 - weight $(t-1) \leq \pi_-$ the new weight is π_-
 - weight (t-1) $\geq \pi_+$ the new weight is π_+
 - weight (t-1) is $\in (\pi_{-}\pi_{+})$ weight does not change.

port1	port2	port3	Market	Date1	Date2
0.42	0.44	0.38	0.09	192801	193801
0.66	0.69	0.76	0.58	193801	194801
1.10	1.12	1.07	1.06	194801	195801
0.76	0.72	0.85	0.89	195801	196801
0.58	0.61	0.50	-0.07	196801	197801
1.06	1.06	0.93	0.40	197801	198801
0.41	0.40	0.49	0.98	198801	199801
-0.03	-0.04	0.01	0.25	199801	200801
0.87	0.61	0.52	0.50	200801	201412

Table 3.13: Sharpe ratio for ten year consecutive windows including transaction cost at 1% for composite portfolio and market

Table (3.13) shows average annual returns and Sharpe ratio before and after accounting for transaction costs with optimal trading. We see that using Gerhold et al. (2014) approach significantly reduces transaction cost impact. At 1% level we can still obtain a Sharpe ratio of 0.62. Which is 50 % higher than the market. Table (3.13) shows Sharpe ratio for the market and composite portfolios over consecutive ten year periods.

Chapter 4

Conclusion

The empirical results in this thesis contribute to the efforts of investors and academics to better diversify risk and build better portfolios. The composite portfolios low volatility and relatively high risk-adjusted returns allow to better diversifying risk. The short side of the 2nd, 3rd, 4th and 5th principal components can be used to reduce exposure to momentum and size and market, and increase exposure to value factors, and they can reduce exposure to industries that have high weights in first component and hence the market.

By excluding the first principal component and investing in the remaining principal components, composite portfolios reduce the exposure to market, and also to firms of industry sectors that had very high/low covariances in the previous year. This limits realized drawdowns in recessions. In view of their transparent construction methodology and their tactical exposure to industry sectors during recessions, principal components offer quantitative strategies with accessible and attractive characteristics.

In this thesis, we examine single principal components and record their characteristics over eighty eight years; we also constructed equal weights composite portfolios which have shown potential. Further research studies will explore the potential of these principal portfolios with the risk parity approach. Chapter 5

Appendix

5.1 Appendix A:Returns Calculations

D-tab and **M-tab** are Our main daily and monthly data files respectively they includes: PERMNO prices number of outstanding shares amount of Ordinary dividends returns Risk free rates from Fama and french Library (link). we add a new column which contain the total excess returns in each time stamp which we calculated as follows:

a) If the number of outstanding shares does not change for two consecutive time stamps and the price at time (t-1) is not zero

total Excess Returns =
$$\frac{P_t + Div_t - P_{t-1} - RF_t}{P_{t-1}}$$

b)If the number of outstanding shares changes in a two consecutive time (either consolidation or dilution):

• The price at time (t-1) is not zero

Total Excess Returns =
$$Ret_t - RF_t + \frac{Div_t}{P_{t-1}}$$

• The price at time (t-1) is zero

Total Excess Returns = $Ret_t - RF_t$

 Ret_t as given by CRSP

We primarly use **D-tab** to calculate covariance matrix and compute eigenvlaues and vectors and **M-tab** to calculate portfolios monthly returns.

5.2 Appendix B:Transactions Costs Function

By solving this equation we can obtain returns after accounting for transaction costs \mathbf{r}^x_t .

```
In R language we use this function:
retrans = function (pi0, pi1, rets, safe, eps, dt) {
uniroot (
function (rx) sum(pi0*rets) + safe*dt*(1-sum(pi0)) - sum(eps*abs(pi1*(1+rx)-pi0*(1+rets)))
- rx c(-1 10))$root}
```

5.3 Appendix D:Tables and Graphs

5.4 Appendix E: Portfolio Industry Composition

Table 5.1: Composite portfolio-1 components industry weights 2008, a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC, LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

m-indus	date	a-p2TOT	a-p3SH	a-p4SH	a-p5TOT	m6-p2LO	m6-p4LO	total	inds-ret	a-p1TOT
Banks	200806	-0.155	-0.332	-0.275	0.024	0.001	0.116	-0.106	-45.39	0.055
Fin	200806	-0.09	-0.249	-0.243	-0.059	0.024	0.148	-0.08	-59.21	0.069
Rtail	200806	-0.03	-0.137	-0.106	-0.193	0.008	0.149	-0.053	-20.9	0.051
Trans	200806	-0.004	-0.034	-0.059	-0.154	0.018	0.08	-0.026	-23.83	0.022
Chips	200806	0.028	-0.024	-0.049	-0.226	0.1	0.066	-0.018	-44.26	0.052
Meals	200806	0.018	-0.044	-0.032	-0.047	0	0.038	-0.011	-17.7	0.014
Hardw	200806	0.003	-0.012	-0.02	-0.096	0.031	0.039	-0.009	-45.5	0.019
Clths	200806	-0.004	-0.024	-0.017	-0.023	0.003	0.017	-0.008	-32.97	0.01
Autos	200806	0.029	-0.009	-0.016	-0.068	0.005	0.018	-0.007	-63.66	0.013
BusSv	200806	-0.032	-0.048	-0.159	-0.035	0.052	0.179	-0.007	-36.48	0.047
Cnstr	200806	-0.008	-0.026	-0.028	-0.02	0.031	0.01	-0.007	-42.53	0.015
Fun	200806	-0.012	-0.012	-0.011	-0.019	0.005	0.008	-0.007	-69.18	0.01
Books	200806	0	-0.012	-0.024	-0.002	0.002	0.015	-0.003	-60.36	0.006
Softw	200806	0.044	-0.021	-0.052	-0.151	0.051	0.111	-0.003	-40.62	0.048
Paper	200806	0.018	-0.005	-0.013	-0.027	0.011	0.008	-0.001	-41.78	0.008
RlEst	200806	0.004	-0.006	-0.007	-0.009	0.005	0.007	-0.001	-66.94	0.003
Agric	200806	-0.005	-0.003	-0.003	0.002	0.003	0.007	0	-36.78	0.002
Guns	200806	0.006	-0.002	-0.003	-0.007	0.002	0.002	0	-20.43	0.002
Hshld	200806	0.006	-0.016	-0.019	-0.011	0.004	0.038	0	-20.87	0.01
Insur	200806	0.037	-0.126	-0.144	0.027	0.006	0.199	0	-49.02	0.034
Txtls	200806	-0.01	-0.008	-0.005	0.007	0.002	0.013	0	-50.05	0.003
Smoke	200806	0.002	-0.002	-0.004	0.003	0.001	0.007	0.001	-24.29	0.001
Toys	200806	0.01	-0.001	-0.004	-0.014	0.006	0.012	0.001	-31.37	0.003
Aero	200806	0.014	0	-0.009	-0.019	0.009	0.017	0.002	-44.24	0.005
Beer	200806	0	-0.001	-0.001	0	0.001	0.011	0.002	-16.54	0.001
Ships	200806	0.003	-0.001	-0.002	0.004	0.002	0.004	0.002	-34.58	0.002
Soda	200806	0.012	-0.005	-0.013	0.004	0.001	0.015	0.002	-43.69	0.002
Telcm	200806	0.08	-0.013	-0.03	-0.101	0.031	0.048	0.002	-35.41	0.026
unkwn-bnkrpt	200806	0.009	-0.003	-0.012	0.01	0	0.007	0.002	NA	0.003
Boxes	200806	0.012	-0.006	-0.013	0	0.005	0.019	0.003	-29.24	0.006
PerSv	200806	-0.01	-0.017	-0.019	-0.001	0.006	0.06	0.003	-20.49	0.01
Other	200806	0.004	-0.004	-0.001	0.001	0.006	0.016	0.004	-49.53	0.003
FabPr	200806	-0.001	-0.003	-0.001	0.01	0.009	0.013	0.005	-39.97	0.004
Rubbr	200806	0.018	-0.007	-0.013	0.008	0.007	0.019	0.005	-35.4	0.005
BldMt	200806	0.009	-0.008	-0.012	-0.007	0.024	0.038	0.007	-41.26	0.014
Gold	200806	0.004	0	0	0.019	0.015	0.003	0.007	-24.17	0.002
Hlth	200806	-0.022	-0.013	-0.025	0	0.007	0.094	0.007	-35.24	0.012
ElcEq	200806	0.014	-0.007	-0.022	-0.003	0.029	0.04	0.009	-42.21	0.016
MedEq	200806	-0.012	-0.01	-0.021	0.003	0.013	0.087	0.01	-32.98	0.015
Mines	200806	-0.008	-0.002	0	0.034	0.024	0.011	0.01	-55.81	0.007
Food	200806	0.004	-0.014	-0.029	0.028	0.009	0.075	0.012	-17.3	0.012
Drugs	200806	-0.023	-0.025	-0.046	-0.019	0.025	0.166	0.013	-13.06	0.027
Coal	200806	-0.004	-0.001	-0.004	0.049	0.038	0.004	0.014	-62.13	0.004
LabEq	200806	0.007	-0.01	-0.015	0.019	0.012	0.069	0.014	-42.42	0.012
Steel	200806	0.043	-0.007	-0.012	-0.003	0.063	0.015	0.017	-60.26	0.018
Mach	200806	0.025	-0.018	-0.02	0.033	0.071	0.073	0.028	-50	0.031
Whlsl	200806	0.047	-0.045	-0.054	0.029	0.045	0.148	0.029	-35.27	0.034
Chems	200806	0.057	-0.012	-0.033	0.042	0.06	0.075	0.032	-46.87	0.022
Util	200806	-0.001	-0.028	-0.082	0.372	0.043	0.428	0.124	-28.79	0.037
Oil	200806	0.057	-0.011	-0.016	0.591	0.332	0.245	0.203	-33.05	0.042

Table 5.2: Composite portfolio-1 components industry weights 2002, a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC, LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

m-indus	date	a-p2TOT	a-p3SH	a-p4SH	a-p5TOT	m6-p2LO	m6-p4LO	total	inds-ret	a-p1TOT
Telcm	200206	0.024	-0.078	-0.051	-0.176	0.065	0.088	-0.022	-30.62	0.018
Hardw	200206	-0.063	-0.032	-0.055	-0.024	0.013	0.05	-0.019	-30.43	0.024
Softw	200206	-0.031	-0.05	-0.128	0.007	0.053	0.074	-0.013	-35.76	0.061
ElcEq	200206	-0.022	-0.023	-0.02	-0.066	0.033	0.057	-0.007	-7.28	0.016
LabEq	200206	-0.004	-0.021	-0.025	-0.038	0.026	0.057	-0.001	-39.67	0.011
unknown-bankruptcies	200206	0.004	-0.003	-0.002	-0.009	0.008	0.004	0	NA	0.001
Coal	200206	0.001	0	0	-0.001	0.002	0.005	0.001	-13.94	0
Gold	200206	0.001	0	0	0.005	0	0.001	0.001	62.23	0
Mines	200206	0.003	-0.002	0	0.002	0.006	0.005	0.002	-14.14	0.001
Ships	200206	0.003	-0.001	0	0.003	0.004	0.004	0.002	0.48	0
Smoke	200206	0.004	0	0	0	0.004	0.006	0.002	-7.21	0
Soda	200206	0.002	0	-0.001	0.007	0.003	0.002	0.002	12.57	0
Agric	200206	-0.001	-0.002	-0.001	0.005	0.006	0.008	0.003	-5.18	0.001
Beer	200206	0.004	0	-0.001	0.007	0.004	0.005	0.003	-1.56	0
Guns	200206	0.002	-0.002	0	0	0.007	0.009	0.003	22.95	0
Toys	200206	0.003	-0.003	-0.003	0.001	0.012	0.01	0.003	-4.36	0.001
Books	200206	0.012	-0.018	-0.004	-0.003	0.018	0.017	0.004	4.15	0.003
FabPr	200206	0.009	-0.01	-0.005	-0.002	0.017	0.013	0.004	-25.21	0.001
RlEst	200206	0.007	-0.005	-0.003	0.003	0.008	0.011	0.004	-9.84	0.001
Other	200206	0.01	-0.005	-0.001	0.009	0.009	0.009	0.005	-36.01	0.001
Txtls	200206	0.008	-0.006	0	-0.001	0.012	0.018	0.005	-9.5	0.001
Rubbr	200206	0.009	-0.008	0	0.002	0.015	0.016	0.006	-0.1	0.001
Aero	200206	0.009	-0.011	-0.001	0.009	0.017	0.019	0.007	-13.02	0.001
Boxes	200206	0.008	-0.005	-0.001	0.006	0.014	0.017	0.007	16.21	0.001
Chips	200206	-0.157	-0.104	-0.039	0.051	0.038	0.264	0.009	-49.83	0.062
Fun	200206	0.025	-0.024	-0.01	-0.004	0.041	0.024	0.009	-4.37	0.005
PerSv	200206	0.018	-0.01	-0.01	-0.015	0.029	0.043	0.009	-0.19	0.004
Clths	200206	0.014	-0.019	-0.003	0	0.03	0.038	0.01	-2.79	0.002
BusSv	200206	0.084	-0.047	-0.13	-0.071	0.127	0.106	0.012	-37.76	0.028
Drugs	200206	0.136	-0.004	-0.227	-0.007	0.184	0.007	0.015	-23.73	0.024
Food	200206	0.021	-0.007	-0.013	0.033	0.036	0.024	0.016	-0.4	0.002
MedEq	200206	0.029	-0.007	-0.031	0.029	0.056	0.02	0.016	-13.28	0.004
Paper	200206	0.023	-0.026	-0.008	0.012	0.038	0.056	0.016	-5.96	0.004
Steel	200206	0.019	-0.023	-0.007	0.024	0.028	0.054	0.016	-34.84	0.005
Trans	200206	0.06	-0.117	-0.012	-0.004	0.064	0.112	0.018	-0.56	0.01
Hlth	200206	0.056	-0.001	-0.06	0.034	0.077	0.006	0.019	-24.36	0.004
Hshld	200206	0.023	-0.021	-0.006	0.017	0.042	0.058	0.019	4.04	0.003
Autos	200206	0.032	-0.06	-0.014	0.003	0.067	0.098	0.021	-21.55	0.005
Cnstr	200206	0.03	-0.031	-0.004	0.023	0.051	0.074	0.024	-14.35	0.004
BldMt	200206	0.025	-0.027	-0.001	0.015	0.046	0.087	0.025	-8.26	0.004
Chems	200206	0.044	-0.036	-0.014	0.035	0.065	0.087	0.031	-5.54	0.005
Whlsl	200206	0.05	-0.042	-0.025	0.011	0.097	0.092	0.031	-14.77	0.009
Mach	200206	0.022	-0.034	-0.005	0.036	0.066	0.117	0.034	-12.96	0.011
Meals	200206	0.039	-0.053	-0.015	0.032	0.091	0.106	0.034	-17.03	0.006
Banks	200206	0.091	-0.04	-0.131	-0.01	0.164	0.147	0.038	-8.61	0.014
Fin	200206	0.083	-0.063	-0.12	0.019	0.143	0.179	0.041	-25.75	0.02
Insur	200206	0.065	-0.011	-0.041	0.083	0.094	0.063	0.043	-14.6	0.006
Oil	200206	0.097	-0.002	-0.001	0.055	0.083	0.056	0.049	-9.04	0.005
Util	200206	0.082	-0.001	-0.008	0.153	0.093	0.017	0.057	-21.48	0.004
Rtail	200206	0.124	-0.201	-0.078	0.01	0.24	0.304	0.068	-21.83	0.021

Table 5.3: Composite portfolio-1 components industry weights 2000, a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC, LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

m-indus	date	a-p2TOT	a-p3SH	a-p $4SH$	a-p5TOT	m6-p2LO	m6-p4LO	total	inds-ret	a-p1TOT
Softw	200006	-0.027	-0.352	-0.1	-0.104	0.054	0.087	-0.075	-49.82	0.131
Chips	200006	0.091	-0.171	-0.168	-0.266	0.063	0.07	-0.065	-34.14	0.073
Telcm	200006	-0.021	-0.032	-0.116	-0.035	0.045	0.05	-0.019	-39.46	0.058
ElcEq	200006	0.031	-0.07	-0.037	-0.053	0.026	0.019	-0.014	-16.16	0.025
Hardw	200006	0.047	-0.064	-0.065	-0.032	0.023	0.014	-0.013	-26.68	0.029
Agric	200006	0.002	-0.002	-0.008	0	0.003	0.001	-0.001	-5.99	0.001
Gold	200006	0.003	0	0	-0.01	0.002	0	-0.001	-32.51	0
LabEq	200006	0.021	-0.027	-0.025	-0.03	0.008	0.055	0	8.96	0.011
Mach	200006	0.067	-0.03	-0.033	-0.059	0.037	0.019	0	2.04	0.014
Toys	200006	0.01	-0.005	-0.007	-0.005	0.004	0.002	0	-12.72	0.004
Fun	200006	0.002	-0.005	-0.012	0.011	0.007	0.004	0.001	-5.48	0.008
Guns	200006	0.006	-0.003	0	-0.003	0.003	0.002	0.001	44.35	0.001
Soda	200006	0.002	0	-0.001	0.003	0.003	0	0.001	26.31	0
unknown-bankruptcies	200006	0.004	-0.004	-0.001	-0.004	0.004	0.005	0.001	NA	0.001
Beer	200006	0.004	0	-0.005	0.003	0.006	0.002	0.002	17.91	0.001
Mines	200006	0.01	0	-0.001	-0.007	0.005	0.006	0.002	-7.9	0.001
Ships	200006	0.007	0	-0.001	0.002	0.004	0.001	0.002	44.81	0.001
Smoke	200006	0.002	0	-0.001	0.004	0.002	0.003	0.002	102.04	0
Txtls	200006	0.007	0	-0.002	0.001	0.005	0.001	0.002	-6.75	0.001
Aero	200006	0.01	0	-0.003	0.005	0.006	0.001	0.003	23.06	0.001
FabPr	200006	0.01	0	-0.001	0	0.006	0.003	0.003	-13.44	0.001
Other	200006	0.009	-0.001	-0.003	0.007	0.003	0.004	0.003	11.06	0.001
RlEst	200006	0.005	0	-0.001	0.004	0.005	0.005	0.003	-3.94	0.002
Rubbr	200006	0.01	-0.001	-0.002	-0.002	0.007	0.003	0.003	-18.56	0.002
Boxes	200006	0.008	0	-0.002	0.002	0.009	0.005	0.004	-33.83	0.001
Clths	200006	0.011	0	-0.008	0.006	0.011	0.001	0.004	20.42	0.003
PerSv	200006	0.015	-0.009	-0.01	-0.002	0.018	0.013	0.004	-2.04	0.005
Cnstr	200006	0.027	-0.002	-0.016	-0.002	0.018	0.009	0.006	37.4	0.006
Steel	200006	0.043	-0.006	-0.011	-0.019	0.021	0.008	0.006	-9.09	0.005
Books	200006	0.017	-0.01	-0.011	0.022	0.017	0.006	0.007	0.05	0.007
Meals	200006	0.033	-0.003	-0.026	0.014	0.033	0.005	0.01	0.51	0.009
MedEq	200006	0.025	-0.011	-0.023	0.024	0.024	0.019	0.01	30.34	0.009
Trans	200006	0.052	-0.008	-0.053	0.017	0.035	0.015	0.01	6.42	0.013
Autos	200006	0.04	-0.004	-0.018	0.004	0.031	0.01	0.011	-21.94	0.007
Hlth	200006	0.021	-0.008	-0.008	0.021	0.024	0.015	0.011	82.13	0.005
Hshld	200006	0.024	-0.001	-0.009	0.014	0.028	0.006	0.011	-16.65	0.005
Paper	200006	0.034	-0.002	-0.006	0.006	0.028	0.008	0.012	3.05	0.005
BldMt	200006	0.043	-0.002	-0.012	0.006	0.032	0.01	0.013	-4.66	0.003
Food	200006	0.032	-0.003	-0.019	0.03	0.039	0.011	0.015	27.1	0.006
Whlsl	200006	0.061	-0.021	-0.031	0.011	0.049	0.025	0.016	40	0.016
Chems	200006	0.054	-0.001	-0.007	0.005	0.04	0.016	0.018	-4	0.005
Oil	200006	0.1	-0.001	0	-0.073	0.03	0.056	0.019	22.36	0.011
BusSv	200006	0.033	-0.071	-0.067	0.013	0.053	0.195	0.027	-17.13	0.048
Rtail	200006	0.086	-0.031	-0.104	0.076	0.115	0.018	0.027	-18.57	0.035
Insur	200006	0.069	-0.002	-0.053	0.059	0.073	0.024	0.029	41.07	0.011
Util	200006	0.085	-0.004	-0.064	0.084	0.076	0.026	0.034	51.76	0.005
Drugs	200006	0.04	-0.039	-0.059	0.048	0.034	0.252	0.047	36.96	0.025
Fin	200006	0.071	-0.01	-0.111	0.229	0.125	0.019	0.055	16.37	0.044
Banks	200006	0.11	-0.004	-0.089	0.181	0.13	0.028	0.06	22.27	0.027

Table 5.4: Composite portfolio-1 components industry weights 1981, a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC, LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

m-indus	date	a-p2TOT	a-p3SH	a-p4SH	a-p5TOT	m6-p2LO	m6-p4LO	total	inds-ret	a-p1TOT
Oil	198106	-0.216	-0.62	-0.344	-0.794	0.023	0.313	-0.278	-21.34	0.122
Coal	198106	-0.009	-0.006	-0.011	-0.042	0.001	0	-0.011	-11.37	0.003
Agric	198106	-0.004	-0.013	-0.015	-0.001	0.015	0.003	-0.002	12.69	0.005
Mines	198106	-0.112	-0.026	-0.008	0.079	0.03	0.024	-0.002	-6.58	0.012
unknown-bankruptcies	198106	-0.007	-0.005	-0.017	0.012	0.006	0.002	-0.002	NA	0.002
FabPr	198106	0.003	-0.007	-0.002	-0.021	0.012	0.008	-0.001	11.12	0.005
Gold	198106	-0.116	-0.004	-0.001	0.071	0.011	0.032	-0.001	-34.43	0.006
Beer	198106	0.003	-0.013	-0.02	0.01	0.012	0.007	0	17.95	0.004
Soda	198106	0.003	-0.007	-0.009	0.01	0.004	0.001	0	23.98	0.002
Other	198106	0.008	-0.001	-0.004	-0.001	0.004	0.009	0.003	-2.38	0.002
RlEst	198106	0.007	-0.011	-0.011	-0.025	0.022	0.034	0.003	2.08	0.007
Smoke	198106	0.004	-0.001	0	0.002	0.004	0.01	0.003	12.13	0.001
Ships	198106	0.009	-0.012	-0.001	0.01	0.008	0.007	0.004	-31.13	0.004
Toys	198106	0.008	-0.011	-0.01	0.013	0.012	0.009	0.004	-1.75	0.004
Books	198106	0.013	-0.003	-0.012	-0.004	0.026	0.008	0.005	20.58	0.007
Guns	198106	0.01	-0.008	-0.003	0.015	0.004	0.008	0.005	-26.7	0.003
PerSv	198106	0.01	0	-0.006	-0.005	0.017	0.012	0.005	19.53	0.003
Softw	198106	0.01	-0.017	-0.009	0.021	0.018	0.007	0.005	-7.91	0.007
Fun	198106	0.012	-0.013	-0.013	0.022	0.011	0.02	0.007	14.03	0.005
Rubbr	198106	0.005	0	-0.008	0.014	0.02	0.011	0.007	4.29	0.004
Clths	198106	0.004	-0.004	-0.029	0.019	0.044	0.026	0.01	10.76	0.006
Paper	198106	0.012	-0.013	-0.027	0.004	0.033	0.046	0.01	1.61	0.009
Boxes	198106	0.012	-0.01	-0.02	0.022	0.025	0.039	0.012	5.89	0.007
Telcm	198106	0.012	-0.016	-0.057	0.035	0.052	0.041	0.012	33.66	0.013
Hlth	198106	0.018	0	-0.013	0.012	0.028	0.037	0.014	0.31	0.007
BusSv	198106	0.058	-0.032	-0.065	-0.049	0.084	0.091	0.015	5.03	0.028
Aero	198106	0.041	-0.035	-0.017	0.045	0.025	0.038	0.016	-24.82	0.014
Cnstr	198106	0.031	-0.023	-0.009	0.002	0.044	0.05	0.016	-34.84	0.012
Txtls	198106	0.012	-0.002	-0.013	0.026	0.027	0.045	0.016	19.78	0.006
MedEq	198106	0.02	-0.008	-0.038	0.014	0.043	0.067	0.017	5.03	0.011
Steel	198106	0.016	-0.046	-0.019	0.016	0.052	0.088	0.018	-1.28	0.025
Trans	198106	0.076	-0.05	-0.049	-0.008	0.074	0.065	0.018	6.4	0.024
Whlsl	198106	0.03	-0.02	-0.043	0.02	0.066	0.065	0.02	-2.65	0.022
Drugs	198106	0.028	-0.03	-0.054	0.081	0.042	0.061	0.022	4.31	0.012
ElcEq	198106	0.042	-0.026	-0.012	0.015	0.057	0.065	0.024	3.19	0.012
Food	198106	0.032	-0.025	-0.029	0.04	0.061	0.064	0.024	14.48	0.016
Chems	198106	0.041	-0.036	-0.036	0.029	0.056	0.092	0.025	-6.68	0.019
Meals	198106	0.03	-0.033	-0.09	0.113	0.057	0.071	0.025	11.99	0.016
LabEq	198106	0.05	-0.018	-0.014	0.008	0.077	0.055	0.027	-16.13	0.014
Insur	198106	0.032	-0.007	-0.082	0.063	0.095	0.069	0.029	18.97	0.021
Autos	198106	0.041	-0.014	-0.014	0.026	0.07	0.075	0.031	-5.24	0.011
Chips	198106	0.06	-0.067	-0.111	0.079	0.121	0.099	0.031	-7.99	0.041
Hshld	198106	0.032	-0.047	-0.064	0.076	0.079	0.105	0.031	2.58	0.021
Hardw	198106	0.084	-0.073	-0.041	0.09	0.087	0.049	0.033	-16.49	0.029
Mach	198106	0.069	-0.056	-0.047	-0.01	0.08	0.158	0.033	-11.93	0.036
Banks	198106	0.049	-0.019	-0.083	0.07	0.14	0.109	0.045	7.29	0.022
BldMt	198106	0.059	-0.008	-0.032	0.002	0.119	0.124	0.045	-4.91	0.025
Util	198106	0.093	-0.044	-0.102	0.049	0.196	0.15	0.058	6.06	0.033
Rtail	198106	0.079	-0.012	-0.067	0.054	0.172	0.144	0.063	15.69	0.032
Fin	198106	0.114	-0.065	-0.103	0.022	0.269	0.197	0.074	6.81	0.047

Table 5.5: Composite portfolio-1 components industry weights 1973, a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC, LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

m-indus	date	a-p2TOT	a-p3SH	a-p $4SH$	a-p5TOT	m6-p2LO	m6-p4LO	total	$\operatorname{inds-ret}$	a-p1TOT
Chips	197306	-0.078	-0.085	-0.138	0.016	0.05	0.062	-0.03	-30.69	0.056
Hshld	197306	0.071	-0.178	-0.22	-0.07	0.096	0.165	-0.023	-25.26	0.058
Whlsl	197306	0.052	-0.05	-0.14	-0.076	0.06	0.044	-0.019	-34.56	0.042
Drugs	197306	0.03	-0.024	-0.117	-0.065	0.022	0.045	-0.018	-13.07	0.027
Toys	197306	-0.025	-0.052	-0.104	0.042	0.016	0.027	-0.016	-52.28	0.027
MedEq	197306	-0.026	-0.049	-0.066	-0.025	0.033	0.048	-0.014	-19.58	0.023
Oil	197306	0.082	-0.13	-0.074	-0.266	0.133	0.172	-0.014	10.31	0.09
Softw	197306	-0.018	-0.019	-0.006	-0.011	0	0.004	-0.009	-66.89	0.004
Mach	197306	0.059	-0.131	-0.22	-0.014	0.103	0.162	-0.007	-10.4	0.087
ElcEq	197306	0.019	-0.05	-0.133	0.003	0.067	0.064	-0.005	-26.44	0.046
Clths	197306	0.057	-0.057	-0.03	-0.053	0.025	0.032	-0.004	-56.65	0.027
PerSv	197306	0.006	-0.014	-0.046	-0.047	0.033	0.044	-0.004	-55.08	0.013
Fun	197306	-0.007	-0.004	-0.027	0.005	0.011	0.011	-0.002	-59.48	0.017
Hardw	197306	-0.034	-0.03	-0.052	0.038	0.01	0.06	-0.001	-21.6	0.026
Paper	197306	0.029	-0.017	-0.037	-0.048	0.031	0.036	-0.001	5.76	0.008
Food	197306	0.099	-0.104	-0.092	-0.041	0.065	0.074	0	-22.49	0.043
BldMt	197306	0.117	-0.229	-0.198	0.045	0.123	0.147	0.001	-24.82	0.083
Boxes	197306	0.05	-0.03	-0.047	-0.011	0.023	0.022	0.001	-13.64	0.02
FabPr	197306	0.02	-0.013	-0.025	-0.005	0.014	0.012	0.001	1.29	0.004
Guns	197306	-0.002	-0.004	0	0.005	0.006	0.001	0.001	-24.95	0.005
Hlth	197306	0.02	-0.01	-0.056	0.001	0.007	0.044	0.001	-62.24	0.012
Other	197306	0.002	-0.004	-0.003	-0.002	0.003	0.009	0.001	-48.57	0.002
Agric	197306	-0.004	-0.008	-0.016	0.004	0.005	0.029	0.002	-4.18	0.007
Beer	197306	0.01	-0.006	-0.014	-0.006	0.01	0.016	0.002	-16.56	0.008
Coal	197306	0.007	-0.004	0	0.003	0.004	0.005	0.002	9.3	0.003
Meals	197306	0.018	-0.033	-0.101	0	0.035	0.094	0.002	-49.53	0.033
Smoke	197306	0.011	-0.013	-0.008	0.003	0.005	0.016	0.002	-14.39	0.005
Rubbr	197306	0.02	-0.033	-0.021	0.014	0.021	0.014	0.003	-34.62	0.01
RlEst	197306	0.04	-0.027	-0.081	0.002	0.04	0.049	0.004	-55.67	0.024
Ships	197306	0.028	-0.032	-0.009	0.015	0.009	0.013	0.004	48.56	0.007
Txtls	197306	0.055	-0.058	-0.052	-0.01	0.05	0.046	0.005	-41.06	0.029
unknown-bankruptcies	197306	0.001	0	0	0.007	0.009	0.016	0.005	NA	0
Soda	197306	0.01	-0.003	-0.006	0.012	0.01	0.025	0.008	-17.83	0.003
Telcm	197306	0.05	-0.027	-0.061	-0.002	0.034	0.057	0.008	-6.59	0.021
Trans	197306	0.016	-0.082	-0.171	0.107	0.067	0.118	0.009	-28.35	0.067
Mines	197306	0.01	-0.061	-0.025	0.051	0.051	0.033	0.01	33.77	0.016
Books	197306	0.062	-0.036	-0.068	-0.014	0.045	0.074	0.011	-40.22	0.017
Aero	197306	0.013	-0.046	-0.029	0.081	0.033	0.021	0.013	-46.21	0.023
Autos	197306	0.033	-0.082	-0.097	0.02	0.065	0.137	0.013	-41.21	0.051
Gold	197306	0.002	-0.007	-0.007	0.064	0.026	0.006	0.014	67.97	0.002
BusSv	197306	0.052	-0.084	-0.105	0.051	0.104	0.082	0.017	-32.64	0.046
Cnstr	197306	0.052	-0.025	-0.035	0.053	0.025	0.04	0.019	-20.37	0.021
Steel	197306	0.149	-0.155	-0.136	0.113	0.064	0.076	0.019	11.47	0.059
Chems	197306	0.087	-0.084	-0.102	0.036	0.066	0.115	0.02	-5.12	0.05
LabEq	197306	0.065	-0.018	-0.073	0.032	0.037	0.08	0.021	-18.01	0.025
Rtail	197306	0.19	-0.16	-0.294	-0.012	0.183	0.253	0.027	-36.01	0.104
Util	197306	0.143	-0.136	-0.034	0.033	0.086	0.119	0.036	-18.64	0.04
Banks	197306	0.101	-0.071	-0.047	-0.021	0.14	0.132	0.04	-13.27	0.033
Insur	197306	0.061	-0.043	-0.038	0.009	0.08	0.192	0.044	-16.24	0.018
Fin	197306	0.102	-0.101	-0.108	-0.026	0.22	0.302	0.066	-26.36	0.052

Table 5.6: Composite portfolio-1 components industry weights 1969, a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC, LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

m-indus	date	a-p2TOT	a-p $3SH$	a-p4SH	a-p5TOT	m6-p2LO	m6-p4LO	total	inds-ret	a-p1TOT
Rubbr	196906	-0.034	-0.034	-0.024	-0.018	0.017	0.033	-0.01	-30.23	0.015
Whlsl	196906	0.03	-0.097	-0.098	-0.015	0.079	0.055	-0.008	-30.89	0.035
Meals	196906	0.015	-0.049	-0.041	-0.057	0.054	0.049	-0.005	-13.08	0.022
Aero	196906	0.004	-0.115	-0.074	0.014	0.077	0.071	-0.004	-44.7	0.027
Hardw	196906	-0.096	-0.014	-0.039	0.022	0.042	0.065	-0.004	13.21	0.028
Coal	196906	-0.001	-0.01	-0.011	-0.008	0.011	0.005	-0.002	-5.56	0.003
Gold	196906	0.069	-0.09	-0.139	0.082	0.012	0.055	-0.002	-32.49	-0.004
RlEst	196906	0.039	-0.056	-0.049	-0.031	0.009	0.073	-0.002	-18.29	0.013
Fin	196906	0.044	-0.034	-0.1	-0.029	0.069	0.042	-0.001	-16.61	0.034
Softw	196906	-0.009	0	-0.002	0.003	0	0.001	-0.001	-45.51	0.002
Other	196906	0	-0.002	-0.001	-0.006	0.003	0.008	0	-44.79	0
Chips	196906	-0.076	-0.118	-0.073	-0.004	0.099	0.179	0.001	-16.26	0.041
Agric	196906	-0.014	-0.001	-0.017	0.017	0.01	0.014	0.002	-4.3	0.004
ElcEa	196906	-0.015	-0.079	-0.089	0.051	0.07	0.069	0.002	-11.99	0.038
Hlth	196906	0.001	0	0	0.004	0.003	0.004	0.002	NA	0.002
Guns	196906	-0.006	-0.008	-0.005	0.011	0.021	0.003	0.003	-34.26	0.005
Clths	196906	0.079	-0.051	-0.088	-0.011	0.058	0.041	0.004	-31.15	0.025
Soda	196906	0.008	-0.002	-0.009	0.013	0.014	0.001	0.004	8 27	0.002
Telcm	196906	0.045	-0.039	-0.085	-0.018	0.069	0.052	0.004	-6.05	0.002
Ships	196906	0.040	-0.009	-0.000	0.019	0.009	0.002	0.004	-0.00	0.013
Smoke	196906	0.012	-0.003	-0.013	0.013	0.019	0.005	0.005	-0.64	0.003
FabPr	196906	0.000	-0.005	-0.02	0.011	0.013	0.000	0.005	-0.04	0.002
Paper	106006	0.014	-0.000	-0.021	0.002	0.035	0.025	0.000	0.54	0.004
unknown bankruptcios	106006	0.045	-0.039	-0.022	-0.025	0.000	0.040	0.000	-0.54 NA	0.008
Banka	106006	0.05	0.032	-0.002	0.081	0.003	0.023	0.000	7.06	0 023
ModEa	190900	0.03	-0.032	-0.03	-0.081	0.003	0.071	0.007	-7.90	0.023
Duce	190900	0.039	-0.015	-0.01	-0.023	0.045	0.005	0.007	43.21	0.008
Dusov	190900	-0.074	-0.025	-0.095	0.042	0.007	0.132	0.008	-0.95	0.04
Torra	106006	-0.009	-0.007	-0.009	0.018	0.007	0.044	0.008	-35.74	0.009
Fun	190900	0.017	-0.073	-0.037	0.007	0.033	0.031	0.008	-20.85	0.019
F ull Deen	190900	-0.01	-0.038	-0.010	-0.007	0.018	0.112	0.01	-21.70	0.021
Beer	190900	0.026	-0.028	-0.018	0.022	0.029	0.031	0.011	2.12	0.007
Insur	190900	0.015	-0.014	0	0.011	0.031	0.024	0.011	-23.08	0.003
Unstr Lab Ea	190900	0.041	-0.04	-0.039	0.002	0.047	0.062	0.012	-29.05	0.013
LabEq	190900	0.01	-0.002	-0.041	0.002	0.052	0.054	0.013	-3.06	0.019
Books	196906	0.033	-0.013	-0.023	0.008	0.034	0.05	0.015	-18.85	0.009
Food	196906	0.082	-0.11	-0.118	-0.034	0.103	0.167	0.015	-7.42	0.033
Autos	196906	0.062	-0.06	-0.086	0.001	0.079	0.102	0.017	-12.8	0.034
Boxes	196906	0.042	-0.02	-0.072	0.04	0.062	0.053	0.018	-1.49	0.016
Drugs	196906	0.045	-0.021	-0.056	0.008	0.064	0.091	0.022	18.11	0.021
Txtls	196906	0.062	-0.064	-0.067	0.06	0.043	0.1	0.023	-29.64	0.019
Mines	196906	0.054	-0.093	-0.105	0.072	0.041	0.173	0.024	-22.85	0.015
Mach	196906	0.12	-0.117	-0.173	-0.023	0.223	0.162	0.033	-20.53	0.064
Hshld	196906	0.051	-0.092	-0.132	0.107	0.133	0.159	0.038	6.31	0.045
Steel	196906	0.059	-0.168	-0.139	0.203	0.118	0.153	0.038	-19.76	0.056
Trans	196906	0.059	-0.184	-0.072	0.185	0.149	0.134	0.046	-34.46	0.053
Chems	196906	0.096	-0.042	-0.076	0.064	0.115	0.131	0.049	-23.89	0.036
Oil	196906	0.156	-0.178	-0.096	-0.097	0.124	0.388	0.05	-25.13	0.061
BldMt	196906	0.26	-0.061	-0.15	-0.004	0.185	0.08	0.052	-13.3	0.057
Util	196906	0.175	-0.014	-0.075	-0.097	0.219	0.194	0.068	-14.33	0.028
Rtail	196906	0.274	-0.107	-0.21	0.163	0.272	0.213	0.103	-0.27	0.063

Table 5.7: Composite portfolio-1 components industry weights 1931, a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC, LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

m-indus	date	a-p2TOT	a-p3SH	a-p4SH	a-p5TOT	m6-p2LO	m6-p4LO	total	inds-ret	a-p1TOT
Fun	193106	0.004	-0.067	-0.06	0.018	0.008	0	-0.016	-74.4	0.01
Rtail	193106	0.053	-0.072	-0.058	-0.035	0.02	0.031	-0.01	-25.2	0.042
Steel	193106	0.03	-0.058	-0.07	-0.118	0.044	0.124	-0.008	-63.72	0.047
Boxes	193106	0.003	-0.013	-0.028	-0.012	0.005	0.006	-0.007	-38.1	0.009
Chems	193106	0.008	-0.032	-0.043	-0.019	0.011	0.039	-0.006	-40.92	0.021
ElcEq	193106	0.01	-0.02	-0.036	-0.001	0.01	0	-0.006	-46.73	0.013
BusSv	193106	0.006	-0.001	-0.1	0.035	0.001	0.03	-0.005	-64.34	0.004
Coal	193106	-0.008	-0.009	-0.016	-0.011	0.004	0.014	-0.004	-67.18	0.008
BldMt	193106	0.016	-0.024	-0.049	0.006	0.01	0.028	-0.002	-53.69	0.023
Softw	193106	0.003	-0.004	-0.007	-0.004	0	0.001	-0.002	NA	0.003
Whlsl	193106	-0.001	0	0	-0.014	0.001	0.001	-0.002	-60.86	0.002
Drugs	193106	0.007	0	0	-0.018	0.002	0.003	-0.001	-11.41	0.005
Guns	193106	0.003	0	0	-0.015	0.003	0.002	-0.001	NA	0.002
Telcm	193106	0.006	-0.008	-0.012	0.002	0.004	0.003	-0.001	-30.77	0.006
Toys	193106	-0.001	0	0	-0.01	0	0.006	-0.001	-67.55	0.001
unknown-bankruptcies	193106	0	-0.008	-0.014	0.008	0.006	0	-0.001	NA	0.006
Chips	193106	0.001	0	0	0	0	0	0	-62.83	0.002
FabPr	193106	0.002	0	-0.001	-0.006	0.003	0	0	NA	0.004
Gold	193106	0.001	0	-0.001	0.001	0	0	0	NA	0
LabEq	193106	0	0	0	0	0.002	0	0	-40.02	NA
Mach	193106	0.007	-0.019	-0.036	-0.019	0.02	0.044	0	-60.12	0.033
MedEq	193106	0.001	0	0	0.002	0	0	0	-28.78	0.001
Other	193106	0	0	0	0	0	0.001	0	-0.32	NA
Paper	193106	-0.004	0	0	0	0	0.002	0	-61.7	0
Agric	193106	0	0	0	-0.001	0	0.008	0.001	-48.67	0.001
Beer	193106	0.002	-0.003	-0.002	0.008	0.002	0	0.001	-43.07	0.002
Books	193106	-0.001	-0.001	-0.001	-0.012	0.001	0.017	0.001	-65.88	0.001
Cnstr	193106	0.002	-0.005	-0.009	0.009	0.002	0.004	0.001	-64.21	0.003
Meals	193106	0.001	-0.008	-0.021	0.021	0.002	0.01	0.001	-46.16	0.007
RIEst	193106	-0.001	0	0	-0.014	0.004	0.015	0.001	-66.34	0.004
Txtls	193106	0.003	0	0	0.001	0.001	0.003	0.001	-28.56	0.002
Aero	193106	0.004	-0.022	-0.03	-0.005	0.008	0.058	0.002	-29.86	0.011
Soda	193106	0.003	-0.003	-0.002	0.011	0.001	0.003	0.002	NA	0.003
Util	193106	0.034	-0.06	-0.074	-0.027	0.099	0.043	0.003	-39.83	0.048
Fin	193106	0.003	-0.029	-0.022	0.029	0.009	0.035	0.004	-53.55	0.02
Hardw	193106	0.001	-0.003	-0.004	0.002	0.003	0.025	0.004	-43.75	0.005
Insur	193106	0.001	0	0	0.001	0.002	0.017	0.004	-47.64	0.006
Banks	193106	0.007	0	0	0.016	0.001	0.007	0.005	-36.98	0.005
Food	193106	0.016	-0.044	-0.032	0.017	0.019	0.053	0.005	-33.53	0.037
Hshld	193106	0.004	-0.021	-0.03	0.048	0.013	0.019	0.006	-36.51	0.018
Ships	193106	0.008	0	-0.012	-0.003	0.004	0.038	0.006	-58.95	0.009
Smoke	193106	0.002	-0.014	-0.001	0.009	0.004	0.032	0.006	-20.18	0.01
Artes	193100	0.002	0 000	0.059	0.03	0.004	0.009	0.008	-24.27	0.001
Autos	193106	0 004	-0.026	-0.058	0.059	0.033	0.042	0.009	-33.97	0.051
Mines	193106	0.024	-0.006	-0.01	-0.016	0.01	0.08	0.014	-45.33	0.012
	193106	-0.001	-0.039	-0.022	0.056	0.018	0.075	0.015	-45.91	0.057
Irans	193106	-0.062	-0.014	-0.037	0.1	0.033	0.219	0.041	-60.8	0.058

Table 5.8: Composite portfolio-1 components industry weights 2009, a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC, LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

m-indus	date	a-p2LO	a-p4SH	a-p5TOT	m6-p2TOT	m6-p3SH	m6-p4LO	total	inds-ret	a-p1TOT
Banks	200906	0.127	-0.038	-0.205	-0.22	-0.051	0.029	-0.061	9.34	0.025
Fin	200906	0.123	-0.072	-0.149	-0.238	-0.067	0.084	-0.054	56.51	0.031
Cnstr	200906	0.017	-0.084	-0.045	0.006	-0.024	0.025	-0.018	8.86	0.007
Oil	200906	0.001	-0.022	-0.13	0.079	-0.241	0.209	-0.018	13.1	0.022
Steel	200906	0.001	-0.037	-0.026	0.038	-0.056	0.035	-0.008	32.98	0.008
Fun	200906	0.007	-0.071	0.016	0.007	-0.01	0.008	-0.007	56.6	0.005
Mach	200906	0.006	-0.041	-0.047	0.036	-0.035	0.041	-0.007	50.8	0.012
Coal	200906	0	-0.013	-0.023	0.012	-0.036	0.022	-0.006	116.04	0.002
Gold	200906	0	-0.008	-0.018	0.005	-0.01	0.01	-0.004	22.83	0.001
Autos	200906	0.004	-0.037	0.015	0.015	-0.022	0.007	-0.003	90.64	0.004
Meals	200906	0.022	-0.072	0.013	0.026	-0.009	0.005	-0.002	21.97	0.007
Mines	200906	0	-0.005	-0.015	0.006	-0.013	0.016	-0.002	92.86	0.001
Boxes	200906	0.001	-0.008	0.001	0	-0.006	0.003	-0.001	34.93	0.002
Paper	200906	0.003	-0.014	0.007	0.004	-0.01	0.003	-0.001	54.54	0.003
Ships	200906	0.001	-0.008	0	0.002	-0.001	0	-0.001	38.59	0.001
Agric	200906	0.001	-0.006	-0.001	0.004	0	0.003	0	17.76	0.001
BldMt	200906	0.004	-0.028	-0.007	0.023	-0.011	0.016	0	28.33	0.007
Chems	200906	0.001	-0.026	-0.02	0.03	-0.029	0.04	0	61.81	0.009
Clths	200906	0.01	-0.022	-0.003	0.016	-0.003	0.002	0	52.09	0.003
FabPr	200906	0.001	-0.003	-0.004	0.006	-0.005	0.007	0	41.45	0.001
RlEst	200906	0.003	-0.001	-0.005	-0.003	-0.004	0.011	0	90.07	0.002
Txtls	200906	0.003	-0.005	-0.005	0.005	0	0.001	0	41.88	0.001
Beer	200906	0	0	0.007	0.001	0	0	0.001	21.13	0
Guns	200906	0	0	0.002	0.003	-0.002	0.001	0.001	-4.59	0.001
Smoke	200906	0	0	0.007	-0.001	-0.003	0.003	0.001	27.71	0.001
Toys	200906	0.002	-0.004	0.003	0.005	-0.001	0.001	0.001	27.1	0.001
unknown-bankruptcies	200906	0.001	-0.007	0.006	0.008	-0.003	0.001	0.001	NA	0.001
Aero	200906	0.001	-0.003	0.007	0.011	-0.007	0.003	0.002	36.04	0.003
Books	200906	0.004	-0.008	0.02	0.004	-0.005	0.001	0.002	55.6	0.002
Chips	200906	0.005	-0.101	0	0.107	-0.054	0.053	0.002	50.4	0.018
Other	200906	0.001	-0.002	0.005	0.006	-0.003	0.003	0.002	4.55	0.001
Rubbr	200906	0.002	-0.004	0.007	0.005	-0.005	0.007	0.002	33.32	0.001
Soda	200906	0.001	0	0.007	0.004	0	0.002	0.002	61.01	0.001
PerSv	200906	0.007	-0.014	0.005	0.015	-0.002	0.005	0.003	9.88	0.004
Hshld	200906	0.007	-0.006	0.014	0.011	0	0.005	0.005	12.88	0.004
LabEq	200906	0.002	-0.013	0.019	0.021	-0.006	0.012	0.006	43.93	0.004
ElcEq	200906	0.003	-0.014	0.005	0.033	-0.007	0.019	0.007	29.67	0.006
Hardw	200906	0.003	-0.023	0.023	0.027	-0.01	0.026	0.008	71.14	0.006
Insur	200906	0.027	-0.027	0.111	-0.085	-0.038	0.057	0.008	15.11	0.016
Food	200906	0.006	-0.016	0.039	0.015	-0.004	0.029	0.012	19.44	0.005
Whlsl	200906	0.014	-0.034	0.023	0.054	-0.028	0.043	0.012	42.24	0.012
Trans	200906	0.041	-0.024	0.024	0.042	-0.022	0.018	0.013	24.86	0.01
MedEq	200906	0.003	-0.012	0.048	0.022	0	0.021	0.014	31.36	0.006
Hlth	200906	0.005	-0.012	0.056	0.029	-0.008	0.023	0.016	35.75	0.006
Telcm	200906	0.003	-0.056	0.107	0.025	-0.019	0.036	0.016	26.19	0.011
BusSv	200906	0.016	-0.056	0.062	0.04	-0.009	0.058	0.019	28.37	0.018
Softw	200906	0.008	-0.033	0.047	0.052	-0.007	0.055	0.021	61.38	0.016
Rtail	200906	0.057	-0.102	0.065	0.077	-0.009	0.046	0.023	29.61	0.018
Util	200906	0.002	-0.005	0.113	0.051	-0.034	0.06	0.032	14.71	0.015
Drugs	200906	0.007	-0.017	0.157	0.053	-0.017	0.048	0.039	18.54	0.012

Table 5.9: Composite portfolio-1 components industry weights 2003, a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC, LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

m-indus	date	a-p2TOT	a-p3SH	a-p $4SH$	a-p5TOT	m6-p2LO	m6-p4LO	total	inds-ret	a-p1TOT
Chips	200306	-0.226	-0.191	-0.104	-0.027	0.019	0.349	-0.031	80.4	0.057
Telcm	200306	-0.018	-0.014	-0.182	0.027	0.067	0.036	-0.014	15.55	0.021
Softw	200306	-0.111	-0.042	-0.027	-0.038	0.042	0.148	-0.005	30.82	0.045
Cnstr	200306	0.045	-0.051	-0.045	-0.018	0.045	0.015	-0.002	89.71	0.008
Gold	200306	0.003	-0.002	-0.011	-0.006	0.002	0.003	-0.002	55.51	0
Hlth	200306	0.033	0	-0.007	-0.136	0.057	0.04	-0.002	25.7	0.006
Coal	200306	0.002	-0.002	-0.007	-0.003	0.003	0.009	0	58.57	0.001
Guns	200306	0.005	0	-0.003	-0.005	0.004	0.006	0.001	-8.42	0.001
Ships	200306	0.003	-0.001	-0.004	0.005	0.004	0	0.001	19.97	0.001
Aero	200306	0.011	-0.006	-0.008	-0.004	0.016	0.004	0.002	43.15	0.002
Mines	200306	0.003	-0.002	-0.001	0.003	0.007	0.002	0.002	100.51	0
Txtls	200306	0.005	-0.006	-0.002	0.011	0.003	0.004	0.002	27.04	0.001
Hardw	200306	-0.066	-0.054	-0.008	0.018	0.024	0.106	0.003	59.71	0.021
Other	200306	0.007	-0.005	-0.01	0.001	0.009	0.015	0.003	32.3	0.002
Smoke	200306	0.005	-0.001	-0.002	-0.001	0.008	0.01	0.003	41.58	0.001
Toys	200306	0.005	-0.008	-0.008	0.011	0.007	0.01	0.003	35.1	0.003
unknown-bankruptcies	200306	0.006	-0.002	0	0	0.009	0.003	0.003	NA	0.001
Beer	200306	0.006	0	0	0.003	0.007	0.004	0.004	16.97	0
Soda	200306	0.004	-0.001	0	0.003	0.007	0.008	0.004	1.2	0
Steel	200306	0.013	-0.034	-0.033	0.021	0.024	0.035	0.004	77.31	0.007
Agric	200306	0.002	-0.004	0	0.003	0.011	0.017	0.005	41.59	0.001
Autos	200306	0.046	-0.057	-0.042	0	0.064	0.018	0.005	59.93	0.01
Boxes	200306	0.011	-0.007	-0.003	0.002	0.013	0.014	0.005	13.08	0.002
Clths	200306	0.013	-0.025	-0.003	0.016	0.016	0.011	0.005	39.03	0.003
FabPr	200306	0.007	-0.002	-0.004	0.008	0.008	0.012	0.005	29.64	0.002
Rubbr	200306	0.008	-0.007	-0.008	0.012	0.013	0.012	0.005	2.31	0.003
Fun	200306	0.012	-0.007	-0.015	-0.016	0.042	0.021	0.006	36.12	0.007
RlEst	200306	0.007	-0.003	-0.003	0.008	0.01	0.015	0.006	38.24	0.002
ElcEq	200306	-0.011	-0.021	-0.012	-0.014	0.018	0.083	0.007	44.78	0.012
Oil	200306	0.066	-0.008	-0.077	-0.187	0.071	0.188	0.009	25.93	0.015
BldMt	200306	0.03	-0.039	-0.023	0.02	0.046	0.025	0.01	33.01	0.007
Hshld	200306	0.027	-0.032	-0.009	0.003	0.046	0.02	0.01	15.6	0.006
LabEq	200306	-0.017	-0.022	-0.012	-0.005	0.013	0.102	0.01	56.28	0.01
Books	200306	0.02	-0.004	-0.01	0	0.038	0.021	0.011	19.5	0.005
Util	200306	0.085	-0.001	-0.329	0.08	0.125	0.108	0.012	25.84	0.021
Meals	200306	0.06	-0.035	-0.009	-0.05	0.051	0.058	0.013	37.7	0.01
Mach	200306	0.028	-0.053	-0.03	-0.001	0.058	0.078	0.014	47	0.016
Paper	200306	0.029	-0.037	-0.011	0.044	0.044	0.02	0.015	34.02	0.006
PerSv	200306	0.026	-0.014	-0.005	0.024	0.042	0.034	0.018	45.03	0.005
Drugs	200306	0.007	0	-0.031	-0.079	0.145	0.073	0.02	18.36	0.025
MedEq	200306	0.032	-0.005	-0.013	-0.007	0.06	0.06	0.022	35.79	0.008
Rtail	200306	0.15	-0.23	-0.024	-0.07	0.181	0.125	0.022	29.15	0.032
Trans	200306	0.042	-0.051	-0.064	0.091	0.09	0.041	0.025	22.97	0.014
BusSv	200306	0.035	-0.054	-0.087	0.011	0.128	0.128	0.027	31.88	0.034
Food	200306	0.033	-0.003	0	0.035	0.058	0.038	0.028	7.56	0.003
Insur	200306	0.085	-0.022	-0.041	-0.048	0.133	0.064	0.029	24.08	0.015
Whlsl	200306	0.067	-0.043	-0.041	0.031	0.096	0.092	0.034	28.4	0.015
Chems	200306	0.051	-0.019	-0.003	0.066	0.07	0.051	0.037	26.54	0.01
Fin	200306	0.111	-0.044	-0.054	0.09	0.188	0.218	0.086	48.27	0.035
Banks	200306	0.139	-0.013	-0.038	0.2	0.172	0.254	0.121	34.02	0.032

Table 5.10: Composite portfolio-1 components industry weights 1975, a: in strategy names stands for annual portfolios, m6: stands for semi-annual portfolios and TOT: stands for total side i.e. regular PC, LO: stands for long side (includes only positive weights), SH: stands for short (includes only negative weights)

m-indus	date	a-p2TOT	a-p3SH	a-p $4SH$	a-p5TOT	m6-p2LO	m6-p4LO	total	inds-ret	a-p1TOT
Meals	197506	-0.03	-0.037	-0.053	-0.029	0.029	0.028	-0.016	116.21	0.016
Trans	197506	0.009	-0.058	-0.079	-0.033	0.048	0.039	-0.013	41.88	0.029
Hardw	197506	-0.008	-0.016	-0.051	-0.001	0.017	0.023	-0.006	39.92	0.011
BusSv	197506	0.025	-0.046	-0.056	-0.055	0.037	0.068	-0.005	41.76	0.025
PerSv	197506	0.003	-0.009	-0.033	-0.004	0.009	0.004	-0.005	38.98	0.003
Boxes	197506	0.01	-0.014	-0.023	-0.027	0.023	0.007	-0.004	29.19	0.01
Aero	197506	0.002	-0.015	-0.029	-0.012	0.012	0.026	-0.003	76.1	0.008
Autos	197506	0.002	-0.03	-0.069	-0.013	0.051	0.048	-0.002	72.14	0.019
Coal	197506	-0.016	0	-0.016	-0.01	0	0.031	-0.002	67.98	0.004
LabEq	197506	0	-0.019	-0.029	0	0.024	0.009	-0.002	59.4	0.007
Agric	197506	-0.006	0	-0.012	-0.003	0.003	0.01	-0.001	18.17	0.002
Beer	197506	-0.002	-0.005	-0.008	0.001	0.008	0.002	-0.001	37.22	0.005
Toys	197506	0.003	-0.006	-0.02	0.005	0.007	0.008	-0.001	52.6	0.003
MedEq	197506	-0.012	-0.02	-0.035	0.011	0.013	0.046	0	20.05	0.012
Ships	197506	0.004	-0.005	-0.013	0.006	0.005	0.004	0	13.6	0.003
Softw	197506	-0.005	0	0	-0.001	0.002	0.002	0	54.11	0.001
Chips	197506	-0.021	-0.017	-0.057	0.004	0.03	0.065	0.001	70.7	0.013
Fun	197506	-0.002	-0.005	-0.023	0.02	0.002	0.012	0.001	119.09	0.004
Smoke	197506	0.004	-0.002	-0.002	-0.004	0.007	0.003	0.001	22.38	0.002
Drugs	197506	-0.021	-0.016	-0.008	-0.012	0.023	0.045	0.002	6.46	0.018
Gold	197506	0.04	0	-0.006	-0.042	0.016	0.003	0.002	-4.34	0
Hlth	197506	0.004	0	-0.021	0.023	0.004	0	0.002	97.8	0.003
Other	197506	0.001	-0.005	-0.008	0.008	0.006	0.012	0.002	29.5	0.002
Soda	197506	-0.002	-0.001	-0.008	-0.002	0.011	0.011	0.002	68.46	0.003
unknown-bankruptcies	197506	-0.008	0	0	0.008	0.002	0.008	0.002	NA	0.002
Cnstr	197506	0	-0.016	-0.026	-0.003	0.025	0.038	0.003	39.75	0.01
ElcEq	197506	0.025	-0.027	-0.067	-0.012	0.043	0.054	0.003	44.71	0.017
FabPr	197506	0.008	-0.004	-0.003	-0.001	0.008	0.008	0.003	15.01	0.003
Guns	197506	0.001	-0.001	-0.01	0.003	0.005	0.019	0.003	41.14	0.002
Rubbr	197506	0.01	-0.007	-0.008	0.002	0.013	0.022	0.005	67.91	0.003
Chems	197506	-0.009	-0.032	-0.07	0.047	0.05	0.051	0.006	49.85	0.026
Mines	197506	0.018	-0.005	-0.025	0.015	0.02	0.012	0.006	38.18	0.006
RlEst	197506	0.014	-0.021	-0.032	0.028	0.03	0.016	0.006	30.75	0.005
Mach	197506	0.051	-0.067	-0.13	-0.017	0.111	0.099	0.008	40.24	0.04
Telcm	197506	0.031	-0.027	-0.063	0.007	0.036	0.062	0.008	25.43	0.012
Steel	197506	0.017	-0.03	-0.099	0.021	0.063	0.08	0.009	36.8	0.027
Clths	197506	0.035	-0.02	-0.054	0.011	0.042	0.04	0.01	115.51	0.008
Hshld	197506	0.009	-0.039	-0.062	0.008	0.064	0.08	0.01	41.33	0.027
Food	197506	0.048	-0.039	-0.086	0.046	0.058	0.037	0.011	52.64	0.021
Paper	197506	0.028	-0.01	-0.032	0.013	0.027	0.038	0.011	64.31	0.008
Whlsl	197506	0.025	-0.02	-0.075	0.044	0.048	0.047	0.012	50.88	0.017
Txtls	197506	0.044	-0.018	-0.058	-0.004	0.046	0.071	0.014	73.49	0.009
BldMt	197506	0.085	-0.067	-0.124	-0.078	0.133	0.15	0.017	58.58	0.034
Books	197506	0.029	-0.012	-0.021	0.035	0.037	0.031	0.017	67.79	0.008
Banks	197506	0.051	-0.048	-0.076	0.037	0.124	0.087	0.03	18.18	0.035
Insur	197506	0.022	-0.031	-0.027	0.075	0.067	0.091	0.034	22.35	0.024
Rtail	197506	0.143	-0.081	-0.128	0.044	0.198	0.098	0.047	64.4	0.037
Util	197506	0.223	-0.082	-0.212	-0.075	0.148	0.287	0.049	44.95	0.045
Oil	197506	0.031	-0.041	-0.186	0.237	0.034	0.265	0.058	23.51	0.068
Fin	197506	0.151	-0.1	-0.12	0.1	0.201	0.124	0.06	24.08	0.058

Chapter 6

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