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Strategic Allocation to Return Factors

Master Thesis

Banking & Finance

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Executive Summary

Diversification is one of the most fundamental concepts in asset management theory and practice. However, during the financial crisis many private and institutional investors with diversified portfolios suffered big losses across all asset classes. The increased correlations among asset classes during big economic downturns offset diversification effects. As a result, Bhansali (2011) argued, that investors would be better off by diversifying their exposure across risk factors instead of asset classes. Risk premiums try to explain the fundamental economic rationale for positive excess returns but it is very difficult to find a common framework for their meaningful allocation in portfolios. A pragmatic approach combines empirically proven return sources such as beta, value, momentum, carry and volatility into a strategic allocation and may offer superior diversification benefits. Such "return factors" allow for more straight forward investment proxies and allocation rules than risk premiums.

The existing literature focused more on the identification of individual sources of returns than on the explanation of different portfolio construction approaches for return factor portfolios. On the other hand, there are plenty of studies which document portfolio construction methods for traditional asset class portfolios.

Ilmanen and Kizer (2012) showed that a portfolio determined by various strategy styles offers better diversification benefits than an asset class diversified portfolio. They formed portfolios according to an equal weighted and an equal volatility weighted approach. The equal volatility weighted approach produced a higher Sharpe ratio.

This thesis aims to extend the framework of Ilmanen and Kizer (2012) by analyzing different approaches to construct portfolios consisting of well-known return sources.

In a first step, proxies which track the performance of selected return sources will be described and their market characteristics will be analyzed. The thesis focuses on beta, value, momentum, carry and volatility as return sources. Many of these return sources can be harvested across various asset classes (see Asness, Moskowitz & Pedersen. (2013) and Koijen et al. (2015)).

In a second step, the individual return factors will be combined into portfolios based on the following approaches: Equal weighting, mean variance optimization (Markowitz (1952)), risk parity (Mailard, Roncalli & Teiletche (2008)), most diversified portfolio (Choueifaty & Coignard (2008)) and relative carry (Evstigneev, Hens & Schenk-Hoppé (2016)). The return factor portfolios will be compared to a benchmark portfolio consisting of a traditional asset class allocation.

The empirical analysis - using available market data over a 20-year period starting in 01.1995 until 12.2015 - leads to the conclusion that strategic allocations defined directly across various return sources have several advantages over a traditional allocation across asset classes. The inclusion of various return sources beyond beta increases Sharpe ratios, lowers drawdowns and leads to allocations which are better diversified across macroeconomic shocks.

The various portfolio construction approaches do not show dramatically different Sharpe ratios in the long run. However, comparing the Sharpe ratios during different economic environments shows significant variations. The lowest variation and hence the most robust returns were found for the risk parity portfolio.

The asset management industry would be well advised to consider returns beyond beta, given the strong results of return factor allocations. However, the strategies discussed in this thesis are complex to implement and supervise. In addition, the use of leverage, derivatives and short positions is not suitable for many investors.

Politically driven economic parameters (such as quantitative easing and negative interest rates over a long period) may lead to different results. In the academic literature exist little consensus regarding which return factors should be considered and whether they will continue to be profitable in the future. Further research on this topic might be needed before strategic allocations across return factors can be considered for the broad investment audience.

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1. Introduction

1.1. Motivation

Diversification is one of the most fundamental concepts in asset management theory and practice. However, during the financial crisis many private and institutional investors with diversified portfolios suffered big losses across all asset classes. The increased correlations among asset classes during big economic downturns offset diversification effects. As a result, Bhansali (2011) argued, that investors would be better off by diversifying their exposure across risk factors instead of asset classes. Risk premiums try to explain the fundamental economic rationale for positive excess returns but it is very difficult to find a common framework for their meaningful allocation in portfolios. A pragmatic approach is the combination of empirically proven return sources such as beta, value, momentum, carry and volatility in a strategic asset allocation which may offer superior diversification benefits. Such "return factors" allow for more straight forward investment proxies and allocation rules than risk premiums.

Research has shown that the strategic asset allocation policy explains more than 90% of a portfolio's return variation across time (Brinson et al. (1986) and Brinson et al. (1991). In addition, Ang et al. (2009) state in the well-known study on the Norwegian oil fund that risks and return factors explain 99.1% of the funds variation. By defining strategic allocations across return factors for portfolios tackles an investor's problem at its core.

However, the existing literature focused more on the identification of individual sources of returns than on the explanation of different portfolio construction approaches for return factor portfolios. On the other hand, there are plenty of studies which document portfolio construction methods for traditional asset class portfolios.

Ilmanen and Kizer (2012) showed that a portfolio consisting of various strategy styles offers better diversification benefits than an asset class diversified portfolio.

They formed portfolios according to an equal weighted and an equal volatility weighted approach. The equal volatility weighted approach produced a higher Sharpe ratio.

This thesis aims to extend the framework of Ilmanen and Kizer by analyzing different approaches to construct portfolios consisting of well-known return sources.

1.2. Research Question

Based on an empirical analysis the thesis provides insights into following research questions:

- What are the main benefits and drawbacks of a strategic allocation defined directly across return sources?
- How sensitive are the measured results towards different portfolio construction methods?
- What are the implied suggestions for the asset management industry and relevant directions for further research?

1.3. Risk or Return Factors?

A growing literature postulates that investors would be better off by diversifying their investment exposure across risk factors instead of asset classes (Asl and Etula (2012), Bender et al. (2013) and Bhansali (2014)). In addition, the popularity of smart beta strategies (also known as alternative beta or strategic beta) has risen within the asset management industry. However, many studies and smart beta products do not address the very fundamental question whether the investigated factors are in fact risk premiums or rather empirically proven return sources which might be related to market mispricing.

Risk premiums are the compensation for the exposure to a systematic economic risk. Although there are multiple risk factors, they share one key rationale. Factors or assets which perform purely in bad times like recessions and financial crisis warrant a high risk premium. Safe haven assets like government bonds deserve a low risk premium and hence have lower long term returns (Cochrane (2009) and Ilmanen (2011)).

Whereas the view of risk premiums is in line with efficient capital markets, the view of return sources is not necessarily in line. The view of return sources follows a pragmatic approach and acknowledges the existence of multiple sources of returns beyond beta (broad market exposure). These returns can be due to risk premiums or due to market inefficiencies like supply and demand effects or behavioral biases.

Unfortunately, the design of a proxy which captures only one risk premium is not always straightforward. Moreover, it is very difficult to find a common framework to allocate risk premiums into portfolios. As an example, volatility is not a risk premium and therefore portfolio allocation rules which focus on volatility as a risk measure such as mean-variance optimization or risk parity would be inconsistent with the theory of risk premiums. Changing the risk measure for instance to the conditional value-at-risk does not solve the problem either because the conditional value-at-risk does also not classify as a risk premium[1].

On the other hand, a pragmatic approach which combines empirically proven return sources such as beta, value, momentum, carry and volatility might offer superior diversification benefits. Such "return factors" allow for more straight forward investment proxies and allocation rules than risk premiums. Therefore, in view of the above discussed aspects the focus of this thesis will be on return factors.

[1] Although the conditional value at risk is for many investors or risk professionals a better risk measure than volatility because it focuses on the loss and is a coherent measure, it still does not take the timing of losses into account. As stated earlier, it is very important that the losses of an asset occur during bad economic times because only then a high risk premium is warranted (Cochrane 2009)

1.4. Limitations

There exists a huge amount of research papers which document strategies or factors with positive excess returns. Harvey et al. (2014) counted an exponentially increasing number of such papers which amounted in total to more than 300. All of them claiming to show statistically significant strategies or factors. Cazalet and Roncalli (2014), Jacobs and Levy (2014) and Pukthuanthong and Roll (2014) discuss which factors might matter the most. Harvey et al. (2014) suggest that standard significance levels for testing return factors are not appropriate. The standard significance levels do not consider multiple trials and testing. Thus, many of the published factors may only appear to be statistically significant but could be the result of data mining. This thesis focuses on the most widely known and broadly tested sources of returns like carry, value, momentum, volatility and beta. Strategies based on sources of returns are applied across asset classes employing the most common and intuitive methods. It is not part of this thesis to identify the best method for harvesting individual strategy returns.

The next important limitation is related to the forecasting method for the expected risk and return figures which are used as inputs in the portfolio construction process. The forecasts in the empirical analysis are based on the historical sample distribution. The testing of different forecasting approaches is beyond the scope of this thesis.

1.5. Outline

Section 2 gives an overview of the existing literature in relation to factor portfolios. Section 3 discusses different return sources and analyses their performance characteristics. The focus will be on carry, value, momentum, beta and volatility as return sources since they can be harvested across different asset classes (see Asness, Moskowitz & Pedersen. (2013) and Koijen et al. (2015)).

In section 4, the individual return factors will be combined into portfolios based on the following approaches: Equal dollar and equal volatility weighting, mean variance optimization (Markowitz (1952)), risk parity (Mailard, Roncalli &

Teiletche (2008)), maximum diversification (Choueifaty & Coignard (2008)) and relative carry (Evstigneev, Hens & Schenk-Hoppé (2016)). The return factor portfolios will be compared to a benchmark portfolio consisting of a traditional asset allocation. Section 5 discusses implementation issues. The findings and conclusions are given in section 6.

2. Literature Review on Factor Portfolios

It is important to mention that some studies refer to risk factors or risk premiums even though the mentioned factors are rather an investment style or try to exploit a specific market anomaly than a compensation for systematic risk bearing. Nevertheless, the existing literature offers useful insights for analyzing the benefits of a defined strategic asset allocation across return factors.

Bender et al (2010) classify factors per asset class, style and strategy premium. In order to extract the premiums, they form long short factor portfolios across equities, fixed income and currencies. The extracted factors are then combined in an equal weighted portfolio which exhibits significantly less volatility than a traditional asset class portfolio but with similar returns and hence a better Sharpe ratio. The lower volatility is the result of the lower correlation among factors than among asset classes.

Melas et al. (2010) highlights the importance of turnover and transaction costs of factor portfolios. They show that constrained factor mimicking portfolios with a limited number of assets and turnover are still able to track factor returns like value or momentum reasonably well.

Asness, Moskowitz and Pedersen (2013) document the profitability of the value and momentum premium across different asset classes and examine their sensitivity towards different macroeconomic risks. The authors combined the value and momentum premium into a factor portfolio which confirmed the strong diversification benefits due to the negative correlation between the value and the momentum factor.

Idzorek and Kowara (2013) compare factor based allocations with asset class based allocations. Their first analysis is based on an idealized world where the number of factors is equal to the number of asset classes. The authors show that the factor based and asset class based approach are equivalent concepts. The unconstrained mean-variance optimized portfolios are equivalent in terms of risk and returns. The same dimensions of the two approaches lead to a direct relation in returns. In addition, the authors analyzed a real world example consisting of an 8 dimensional asset class space and a 7 dimensional factor space with US data. Depending on the picked time period paper shows that once the efficient frontier generated through risk factors and once the efficient frontier generated through long only asset classes lies above the other one. The authors concluded that none of the approaches is superior in terms of generating a larger opportunity set of portfolios.

Ilmanen and Kizer (2012) compared the performance and average correlations of two portfolios one showing a traditional asset class allocation and the other portfolio showing an allocation considering premiums derived from equity, size, value, momentum, term spread and default risk. The portfolios are equal weighted or equal volatility weighted. Their results are in line with previous studies which document lower average correlation and higher Sharpe ratios for a factor portfolio.

Houweling and van Zundert (2014) used a factor approach for the corporate bond market and found significantly higher Sharpe ratios as compared to a passive corporate bond index. They defined value, size, volatility and momentum factors for a corporate bond portfolio.

Many of these studies have in common that a portfolio consisting of different return sources leads to higher risk adjusted returns than a portfolio consisting of only one return source like a beta portfolio.

3. Return Sources

As mentioned under Section 1.4 Limitations the focus will be on the return sources carry, value, momentum, volatility selling and beta. It is important to mention that these return factors are based on a solid economic rationale from the risk or behavioral finance side, show sufficient out of sample evidence and can be implemented on a large scale with sufficient liquidity.

3.1. Carry

Carry trades are a well-known investment strategy among macroeconomists and currency traders. The rationale of carry trades is based on investing in higher yielding markets and borrowing in lower yielding markets. The most common application can be found in currency markets in which investors are ranking currencies by their short-term interest rate. The carry trader holds a long position in currencies of countries with a higher interest rate and a short position in currencies of countries with a lower interest rate.

Koijen et al. (2015) broaden the concept of carry to other asset classes and show that this investment strategy produces strong returns beyond currency markets. They define carry of an asset as its return if market conditions (e.g. prices) stay the same.

Based on this definition the return of any asset is the sum of its carry, its expected price change and its unexpected price shock. The specialty of carry is its model free characteristic and the ex-ante observability, whereas the expected price change relies on an asset pricing model and is not directly observable in the market.

Traditional economic theory (uncovered interest rate parity) suggests that interest rate differentials would be offset by currency depreciations or appreciations. Hence the return for a currency investor would be the same across currency markets. An economic rationale for carry is the process of balancing out supply and demand across markets. High interest rates can signal excess demand for capital which is not met by local savings and vice versa for low interest rates. However, empirical evidence shows that currency carry strategies can capture the yield differential and on top of it some capital gains. The capital gains are maybe due to dominant non-profit seeking participants in the currency market like central banks which might create inefficiencies in the market due to their political motives (Asness et al. (2015). Other researchers argue that differences in expected currency returns arise from differences in crash risk (Brunnermeier et al. (2008) and Burnside et al. (2011)), differences in consumption risk (Lustig and Verdelhan (2007)), differences in liquidity risk (Brunnermeier et al. (2008)) and from differences in the size of countries (Hassan (2013)).

3.1.1. Data for Carry Composites

To provide empirical evidence of carry returns across asset classes, composite portfolios of carry strategies in equities, fixed income, commodities and currencies are formed. Firstly, the asset class data will be described, then the details on the carry composite construction and the weighting scheme will be shown.

Equities: In the analysis equity index futures data from 13 countries are used (US (S&P 500), Canada (S&P TSE 60), UK (FTSE 100), France (CAC 40), Germany (DAX), Spain (IBEX), Italy, Netherlands (EOE AEX), Sweden (OMX), Switzerland (SMI), Japan (Nikkei), Hong Kong (Hang Seng) and Australia (S&P ASX 200)). Spot, nearest- and second-nearest-to-expiration contracts are downloaded from Bloomberg to calculate the carry. The returns of the future series are derived from first generic future prices using Bloomberg's GFUT settings in order to back adjust (Bloomberg's ratio-setting) the time series for rollover-dates. The series do not include any returns from collateral and are therefore comparable to excess returns[2]. All price series are at a monthly frequency and in USD.

Fixed Income: The analysis includes liquid government bond future contracts from the US, Australia, Canada, Germany, the UK, and Japan. Nearest- and second-nearest-to-expiration contracts are downloaded from Bloomberg to calculate the

[2] Using the underlying stock index return series and subtracting the 1 month US treasury bill rate in order to obtain excess returns, leads to very similar results.

carry. The same procedures as for equity futures are applied to generate the generic excess return series for government bond futures. All price series are at a monthly frequency and the resulting returns are converted to USD.

Commodities: 19 commodity contracts are included in the analysis (Brent crude oil, gasoil, WTI crude, gasoline, heating oil, natural gas, cotton, coffee, cocoa, sugar, soybeans, wheat, corn, lean hogs, feeder cattle, live cattle, gold and silver). Nearest- and second-nearest-to-expiration contracts are used to calculate the carry. The return series are obtained through the corresponding Goldman Sachs Commodity Index (GSCI) for all 19 commodities. The price indices do not contain any returns from collateral and hence are comparable to excess return series. All prices are in USD, at a monthly frequency and from Bloomberg.

Currencies: The currency data consists of spot and 1-month forward price data for the G11 currencies (EUR, AUD, DKK, CAD, JPY, NDZ, NOK, SEK, CHF and GBP). All prices are in USD, at a monthly frequency and downloaded from Bloomberg.

3.1.2. Carry Definition and Methodology

In this section, the methodology for computing the carry of each asset class will be presented. In addition, an economic interpretation of carry for each asset class is given following Koijen et al. (2015).

The general definition of carry is the expected return if market prices would stay the same. It is given by the ratio of spot price (S_t) divided by the forward or future price (F_t) minus 1.

$$C_t = \frac{S_t - F_t}{F_t}$$

Starting with the definition of the most common application of carry, the carry of a currency forward is the return on the forward position if the spot price would not change. Hence the carry can be measured by the forward discount/premium. The no-arbitrage price of a currency forward with spot price S_t (measured in number of local currency units per foreign currency unit), local interest rate r^f and foreign interest rate r^{f*} is given by $F_t = S_t\,(1+r_t^f)/(1+r_t^{f*})$. Hence, the carry of this position is given by:

$$Ct \quad = \frac{S_t - F_t}{F_t} = \frac{r_t^{f*} - \ r_t^f}{1 + r_t^f}$$

Whereas the second equation only holds under covered interest rate parity. The defined carry is in excess of the local risk free rate because forwards are zero-cost instruments.

The carry of equity index futures is defined similarly. The no arbitrage price of an equity future contract is given by the compounded current equity value (S_t* (1+r_t^f)) minus the expected future dividend payment under the risk neutral measure Q ($E_t^Q(D_{t+1})$) (see Van Binsbergen et al. (2012)). Hence the carry for equity futures is defined as:

$$Ct \quad = \frac{S_t - F_t}{F_t} = \left(\frac{E_t^Q(D_{t+1})}{S_t} - r_t^f\right)\frac{S_t}{F_t}$$

Hence the carry of equity index futures is proportional to the expected dividend yield minus the risk free rate. Dividend yields are extensively studied in the literature on value investing. However, the dividend yield in the value literature is often based on past dividends while the future contract based carry relies on expected future dividend payments. Koijen et al (2015) shows that these two measures behave quite differently. Hence the correlation between equity value and equity carry is only 0.17[3].

The arbitrage free price of a future contract is given by $F_t = S_t(1+r_t^f-d_t)$, where d_t is the convenience yield less storage costs. The commodity futures carry is given by:

$$Ct \quad = \frac{S_t - F_t}{F_t} = \left(d_t - r_t^f\right)\left(\frac{1}{1 + r_t^f - d_t}\right)$$

Hence, the application of the general carry definition on commodity futures shows, that its carry is proportional to the convenience yield less storage costs and in

[3] Historical average correlation from 01.1990 until 12.2015. A correlation matrix of all return factors across asset classes is given in the appendix "Correlation Matrix All Return Factors".

excess of the risk free rate. Since commodity spot markets are highly illiquid, many studies use near term future contracts as approximation. Hence instead of calculating the slope of the spot and future contract, the slope between the nearest- and second-nearest to maturity future contract will be examined and scaled to a monthly measure in order to obtain comparable carry estimates across contracts. This procedure sorts contracts according to their level of contango and backwardation whereas the most backwarded contracts yield the most carry. This measure is extensively used in research as commodity return predictor (see Gorton et al. (2007), Fuertes et al. (2010) and Hong and Yogo (2011)).

The carry of government bond futures is defined in the same way as for commodity contracts, hence the slope of the government bond future curve. Koijen et al. (2015) provide an intuitive approximation under the assumption that the entire yield curve stays the same. In this setup, the carry of a bond future is approximately the bond yield plus the "roll down" on the yield curve scaled by its modified duration. The roll down on the yield curve captures the price increase due to the fact that the bond gets closer to maturity.

3.1.3. Carry Trade Portfolios

After computing the carry of the individual contracts, carry portfolios in each asset class can be formed. The individual contracts will be ranked according to their carry. A long position is taken in the high yielding contracts and a short position in the low yielding contracts weighted by their carry ranking. The weight at time t on each contract i is given by:

$$w_t^i = z_t \left(rank\left(C_t^i\right) - \left(\frac{N_t + 1}{2}\right) \right)$$

Where C_t^i is the i^{th} contract's carry at time t, N_t is the number of contracts at time t and z_t is a scaling factor to ensure that the sum of the long and short leg equals plus one and minus one, respectively. The carry trade portfolios are rebalanced monthly.

Hence the carry of the portfolio is the weighted average carry of its constituents and the return of the portfolio is the weighted average return of its constituents.

Asness et al (2013) and Koijen et al. (2015) define weights and portfolio returns for their long short portfolios in a similar way.

3.1.4. Empirical Results of Carry Across Asset Classes

Carry strategy portfolios are constructed for each asset class according to the methodology in the previous sections.

Figure 1 shows the wealth evolution of carry strategies in equities, fixed income, commodities and currencies. Table 1 summarizes performance statistics of carry strategies across asset classes and of corresponding long only passive benchmark portfolios. In general, the results are similar to the findings of Koijen et al (2015).

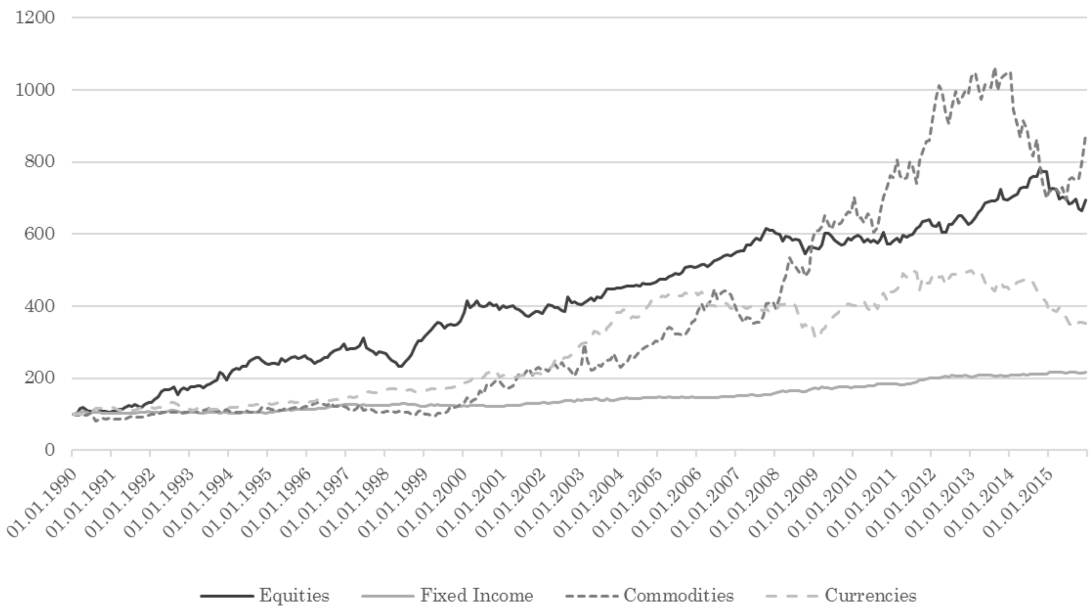

Figure 1: Wealth Evolutions of Carry Across Asset Classes

The Figure shows the wealth evolution of carry strategies in USD for equities, fixed income, commodities and currencies from 01.01.1990 until 31.12.2015. (Source: Own calculations with data from Bloomberg)

The carry strategies generated in all asset classes positive and statistically significant annualized excess returns ranging from 10.22% p.a. for commodities to

3.15% p.a. for fixed income. The Sharpe ratios and the adjusted Sharpe ratios[4] (adjusted for negative skewness and excess kurtosis) are significantly higher for the different carry strategies than for their passive benchmarks except in fixed income. Generally, the carry strategies exhibit small beta exposures towards the passive benchmark portfolio and experience significantly positive alphas. This suggests either the strategy is able to outperform a passive benchmark on a risk adjusted basis or the exposure to other risks of the portfolio is not taken into consideration. In equities and commodities, the strategy exhibits positive skewness. The kurtosis is mildly larger for all carry strategies than for their passive benchmarks, except for commodities which exhibits a mildly smaller skewness. Maximum drawdowns and equity tail returns (defined as the strategies' average monthly performance during the worst 5% or the worst 1% of months for the Fama/French global market factor) are all improved versus the passive benchmark portfolios except for currencies. As a result, a general crash risk explanation for carry returns could be true for currencies but must be rejected as a general explanation for carry returns of other asset classes.

[4] Following Alexander (2008) first order autocorrelation and higher moment adjustments are considered. The standard square root of twelve does not apply for autocorrelated returns. Hence, volatilities are adjusted for first order autocorrelation. Sharpe ratios are adjusted too for autocorrelations since they are the ratio of excess returns over adjusted volatilities. In addition, a second version of Sharpe ratios is also adjusted for higher moments.

Table 1: Summary Statistics of Carry Across Asset Classes

For each carry strategy and its corresponding benchmark ("BM") annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, maximum drawdowns (defined as the strategies' maximum peak-to-trough cumulative loss) and equity tail returns for the 95% and 99% level (defined as the strategies' average monthly performance during the worst 5%, respectively the worst 1% of months for the Fama/French global market factor) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for a linear regression of the individual carry strategy returns on its asset class benchmark (the equity benchmark is the Fama/French global equity market factor, the fixed income benchmark is the Barclays Global Aggregate Bond Index, the commodities benchmark is an equal weighted average of indices for 19 different commodities and the currency benchmark is an equal weighted average of the G11 currencies). Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All returns in this analysis are in USD, after transaction costs and in excess of the risk free rate. All time series are from 31.01.1990 until 31.12.2015 (Source: Own calculations with data from Bloomberg and Kenneth French's website).

	Equities		Fixed Income		Commodities		Currencies	
	Carry	BM	Carry	BM	Carry	BM	Carry	BM
Arithmetic Mean p.a.	8.45%	6.50%	3.15%	3.01%	10.22%	0.34%	5.43%	0.96%
t-statistic	*14.24*	*6.22*	*13.63*	*15.62*	*10.94*	*0.40*	*9.16*	*4.59*
Geometric Mean p.a.	7.88%	4.95%	3.07%	2.96%	8.66%	-0.62%	4.91%	0.90%
Volatility p.a.	10.47%	18.44%	4.09%	3.40%	16.51%	14.88%	10.46%	3.69%
Skewness	0.35	-0.43	-0.36	-0.21	0.30	-0.29	-0.35	0.14
Kurtosis	5.81	4.26	4.01	3.23	4.97	5.29	4.24	4.14
Autocorrelation	0.02	0.09	0.01	0.15	-0.04	0.08	0.06	0.11
Equity Tail Return $_{(95\%)}$	1.25%	-11.15%	1.01%	0.17%	-0.08%	-3.07%	-2.30%	0.12%
Equity Tail Return $_{(99\%)}$	-1.41%	-16.24%	0.01%	-0.78%	1.19%	-7.75%	-1.36%	-0.14%
Max. Drawdown	-25.08%	-56.04%	-7.44%	-8.02%	-34.63%	-55.66%	-31.76%	-11.74%
alpha p.a.	8.50%	-	1.80%	-	10.22%	-	5.88%	-
t-statistic	*3.95*	-	*2.24*	-	*2.92*	-	*3.00*	-
beta	-0.01	-	0.45	-	0.02	-	-0.45	-
t-statistic	*-0.16*	-	*5.96*	-	*0.25*	-	*-2.74*	-
Sharpe Ratio	0.81	0.35	0.77	0.88	0.62	0.02	0.52	0.26
Adj. Sharpe Ratio	0.78	0.34	0.72	0.85	0.62	0.02	0.50	0.26

3.2. Value

The idea of value investing is known for decades and followed by many investors and funds. It goes back to famous value investors like Benjamin Graham and his scholar Warren Buffet. The underlying principle of value investing is based on buying undervalued assets and selling overvalued assets, whereas the cheapness is judged on the ratio of market price to some sort of fundamental value. Many studies use book to market value ratios but the fundamental value can also be beyond book values like sales, earnings or cash flow. Israel and Moskowitz (2013) provide evidence that more measures of value result in more stable portfolios and better return predictability.

There is still a debate among academics why the value premium exists and several risk based as well as behavioral finance based rationales are given. The behaviorists attribute the value premium to behavioral biases like excessive extrapolation of past growth trends into the future and a delayed overreaction to new information (Lakonishok et al. (1994), Barberis et al. (1998) and Daniel et al. (1998)). The risk based explanations state that the value premium might be due to greater default risk in value stocks (Fama and French (1993); (1996) and Campbell et al. (2008)), dynamic betas in the sense that value stocks do not exhibit on average higher betas than growth stocks but during bad times (recessions) they do (Campbell and Vuolteenaho (2004)), or higher long run consumption risk (Hansen et al. (2008) and Malloy et al. (2009)).

Asness et al. (2009) provide broad empirical evidence that value strategies work beyond equity selection in equity country index selection, global government bonds, commodities and currencies. The authors show that value underperforms slightly when long run consumption growth is falling, the current economy weakens, liquidity conditions worsen and credit spreads widen. This helps to justify part of the value premium through the co-movement between value losses and bad economic times. However, the big part of the value premium could not be explained and the authors argue that it might reflect mispricing. The mispricing may persist because transaction costs and liquidity risks limit arbitrageurs to exploit the mispricing.

3.2.1. Value Definition and Methodology

The value returns and the methodology is taken from the study by Asness, Moskowitz and Pedersen (2013) (data updated and maintained by AQR). The data set includes long short value returns for the following asset classes: Global equity indices, global government bonds, commodity futures and currencies.

The authors define value measures for all asset classes. For equity indices, the value measure is the previous month's BE/ME ratio (book value of equity to market value of equity) published for each countries' MSCI Index. For currencies, the value measure is the 5-year change in purchasing power parity. For global government bonds, the value measure is the 5-year yield change of 10-year government bond yields. For commodities, the value measure is the long-term price reversal defined as the log of the average spot price from 4.5 to 5.5 years ago divided by the most recent spot price. These long-term return/reversal measures are originally proposed by DeBondt and Thaler (1985).

The authors form value portfolios for each asset class based on the relative rank of each security within the same asset class. The methodology is similar to the one introduced in the previous section for carry trades. The resulting returns of the zero cost long short value portfolios can be interpreted as excess returns (total returns can be obtained by holding the zero-cost portfolio and investing 100% of the wealth into the risk-free rate).

3.2.2. Empirical Results of Value Across Asset Classes

Figure 2 shows the wealth evolution of value strategies in equities, fixed income, commodities and currencies. Table 2 summarizes performance statistics of value strategies across asset classes and of the corresponding long only passive benchmark portfolios.

The value strategies generated in all asset classes positive and statistically significant annualized excess returns ranging from 2.78% p.a. for currencies to 1.12% p.a. for fixed income. The Sharpe ratios and the adjusted Sharpe ratios (adjusted for negative skewness and excess kurtosis) of the value strategies are higher in commodities and currencies than for their passive benchmarks. However, in equities and fixed income, the Sharpe ratios are significantly lower. Generally, the value strategies exhibit small or even negative beta exposures towards their passive benchmark portfolio but do not show any significant alfas except for value in fixed income.

All value strategies show less severe drawdowns than their passive benchmark during times of large equity market underperformance (measured by the equity tail return). In addition, the value strategies exhibit more positive skewness than their benchmarks. On the other hand, absolute drawdowns are worsened in all asset classes except in equities.

Overall there is a heterogeneous picture of value across asset classes. Also the correlation analysis shows that all pairwise correlations [5] among the value strategies are close to zero. This may suggest that some markets are overvalued or undervalued during different times and that the driving forces of value returns are not the same of all markets.

[5] Historical average correlation from 01.1990 until 12.2015. A correlation matrix of all return factors across asset classes is given in the appendix: “Correlation Matrix All Return Factors”.

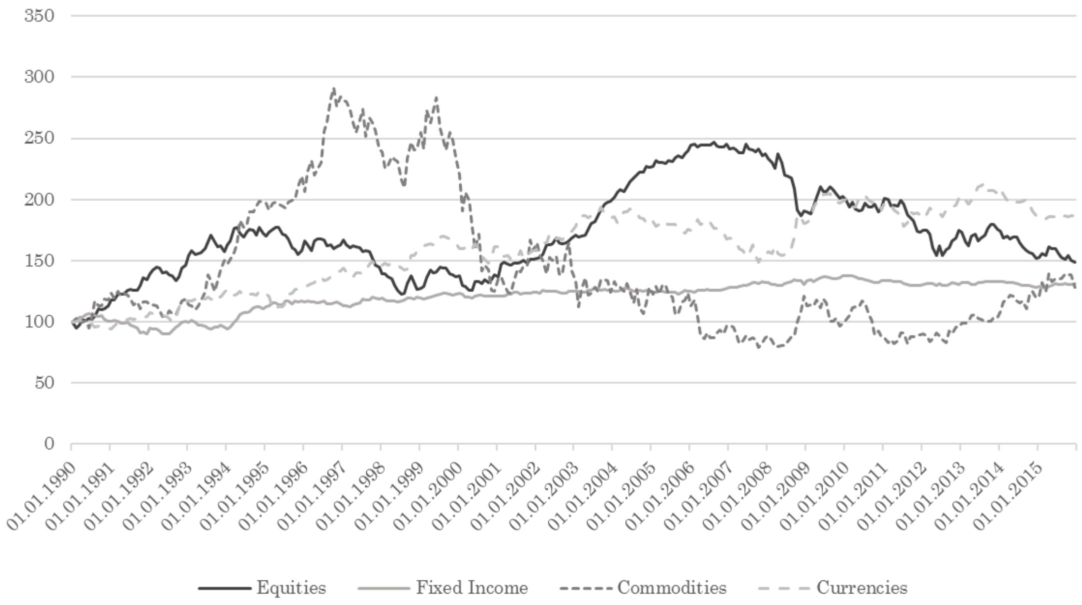

Figure 2: Wealth Evolutions of Value Across Asset Classes

The Figure shows the wealth evolution of excess returns in USD for value strategies in equities, fixed income, commodities and currencies from 01.01.1990 until 31.12.2015. (Source: Own representation with data from Asness, Moskowitz and Pedersen (2013) and AQR)

Table 2: Summary Statistics of Value Across Asset Classes

For each value strategy and its corresponding benchmark ("BM") annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, maximum drawdowns (defined as the strategies maximum peak-to-trough cumulative loss) and equity tail returns for the 95% and 99% level (defined as the strategies average monthly performance during the worst 5%, respectively the worst 1% of months for the Fama/French global equity market factor) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for a linear regression of the individual value strategy returns on its asset class benchmark (the equity benchmark is the Fama/French global market factor, the fixed income benchmark is the Barclays Global Aggregate Bond Index, the commodities benchmark is an equal weighted average of indices for 19 different commodities and the currency benchmark is an equal weighted average of the G11 currencies). Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All returns in this analysis are in USD, after transaction costs and in excess of the risk free rate. All time series are from 31.01.1990 until 31.12.2015 (Source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	Equities		Fixed Income		Commodities		Currencies	
	Value	BM	Value	BM	Value	BM	Value	BM
Arithmetic Mean p.a.	1.74%	6.50%	1.12%	3.01%	2.74%	0.34%	2.78%	0.96%
t-statistic	*3.18*	*6.22*	*4.71*	*15.62*	*2.63*	*0.40*	*5.80*	*4.59*
Geometric Mean p.a.	1.38%	4.95%	1.05%	2.96%	0.82%	-0.62%	2.50%	0.90%
Volatility p.a.	9.68%	18.44%	4.21%	3.40%	18.41%	14.88%	8.48%	3.69%
Skewness	0.12	-0.43	0.83	-0.21	-0.13	-0.29	0.60	0.14
Kurtosis	3.33	4.26	6.39	3.23	3.26	5.29	5.96	4.14
Autocorrelation	0.15	0.09	0.11	0.15	-0.06	0.08	0.13	0.11
Equity Tail Return $_{(95\%)}$	-0.72%	-11.15%	0.08%	0.17%	1.19%	-3.07%	1.26%	0.12%
Equity Tail Return $_{(99\%)}$	-2.17%	-16.24%	-0.18%	-0.78%	3.22%	-7.75%	5.62%	-0.14%
Max. Drawdown	-42.05%	-56.04%	-15.46%	-8.02%	-72.92%	-55.66%	-23.24%	-11.74%
alpha p.a.	1.07%	-	2.30%	-	2.85%	-	2.54%	-
t-statistic	*0.75*	-	*3.05*	-	*0.81*	-	*1.66*	-
beta	0.10	-	-0.39	-	-0.31	-	0.25	-
t-statistic	*3.69*	-	*-5.54*	-	*-4.03*	-	*2.02*	-
Sharpe Ratio	0.18	0.35	0.27	0.88	0.15	0.02	0.33	0.26
Adj. Sharpe Ratio	0.18	0.34	0.27	0.85	0.15	0.02	0.33	0.26

3.3. Momentum

Momentum is referred to the behavior of securities which exhibit persistence in their relative performance. Buying securities when their prices increased in the past and selling securities when their prices decreased could generate profits across many asset classes. Jegadeesh and Titman (1993) belong to the first researchers who document the momentum effect among US equities. Many papers followed and studied the momentum effect in other markets and based on different methodologies.

Similar to value, momentum signals and strategies can be applied beyond just one measure. The most common momentum measure is the price momentum but also fundamental measures like earnings, analyst revisions and changes in profit margins are useful in forming profitable long short portfolios (Asness et al. (2015)).

Adding momentum strategies to a risky portfolio has been a good diversifier, since momentum performed well during equity market meltdown and times of increased volatility (Ilmanen (2011)).

There is an active academic discussion why momentum investing works. Similar to the debate about the value premium, risk based and behavioral based theories exist. Risk based theories argue that high momentum stocks are riskier and therefore offer a compensation for higher risk bearing. For instance, high momentum stocks carry higher growth options which are more vulnerable towards aggregate economic shocks (Berk et al. (1999) and Sagi and Seasholes (2007)) or are more vulnerable towards liquidity risk (Pastor and Stambaugh (2001)).

Gorton, Hayashi and Rouwenhorst (2007) examine momentum returns in commodity markets. The authors document positive correlation between commodity roll returns and commodity momentum returns. They argue that both returns are related to inventory effects. Backwardation in the commodity term structure and high past commodity returns predict low inventories and hence high returns in the future. These returns reflect compensation for higher risk because low inventories have a limited ability to absorb supply and demand shocks, making commodity prices the primary shock absorbers.

3.3.1. Momentum Definition and Methodology

The momentum returns and the methodology is taken from the study by Asness, Moskowitz and Pedersen (2013) (data updated and maintained by AQR). The data set includes long short momentum returns for the following asset classes: Global equity indices, global government bonds, commodity futures and currencies.

Asness Moskowitz and Pedersen (2013) use the 12-month cumulative raw return and skip the most recent month to measure momentum. This momentum measure is standard in the academic literature (see Jegadeesh and Titman (1993), Fama and French (1996) and Grinblatt and Moskowitz (2004)). The most recent month is skipped to avoid the 1-month reversal effect in stock returns, which may be caused by market microstructure or liquidity effects (Jegadeesh (1990), Lo and MacKinlay (1990), Grinblatt and Moskowitz (2004)). This measure is maintained across asset classes for consistency reasons although excluding the most recent month is not necessary for asset classes other than equities because they have less pronounced liquidity issues (Asness Moskowitz and Pedersen (2013)).

The authors form momentum portfolios for each asset class based on the relative rank of each security within the same asset class. The methodology is similar to the one introduced in the previous section about carry and value. The resulting returns of the zero cost long short value portfolios can be interpreted as excess returns.

3.3.2. Empirical Results of Momentum Across Asset Classes

Figure 3 shows the wealth evolution of momentum strategies in equities, fixed income, commodities and currencies. Table 3 summarizes performance statistics of momentum strategies across asset classes and of the corresponding long only passive benchmark portfolios.

The momentum strategies generated in all asset classes positive annualized excess returns ranging from 11.14% p.a. for commodities to 0.22% p.a. for fixed income. All momentum excess returns except the ones for fixed income are statistically significant (99% level and higher). The Sharpe ratios and the adjusted Sharpe ratios (adjusted for negative skewness and excess kurtosis) of the momentum strategies are higher in commodities and equites than for their passive benchmarks. However, in equities and fixed income, the Sharpe ratios are significantly lower. Generally, the momentum strategies exhibit small or even negative beta exposures towards their passive benchmark portfolio. Only the commodity and equity momentum strategies show positive and significant alfas (99% level) versus their benchmarks.

All momentum strategies except in fixed income show less severe drawdowns than their passive benchmark during times of large equity market underperformance (measured by the equity tail return). However, the momentum strategies exhibit on average a higher kurtosis than their benchmarks. Absolute drawdowns are worsened in all asset classes except in equities and commodities.

Overall, momentum was successful in commodities and equities but not in the other analyzed asset classes.

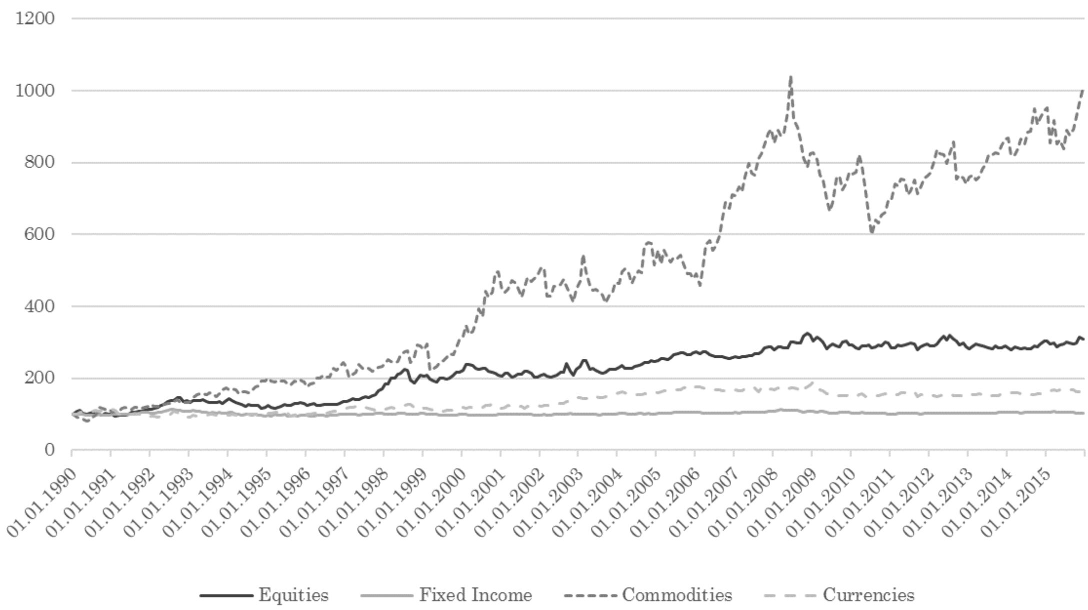

Figure 3: Wealth Evolutions of Momentum Across Asset Classes

The Figure shows the wealth evolution of excess returns in USD for momentum strategies in equities, fixed income, commodities and currencies from 01.01.1990 until 31.12.2015. (source: Own representation with data from Asness, Moskowitz and Pedersen (2013) and AQR)

Table 3: Summary Statistics of Momentum Across Asset Classes

For each momentum strategy and its corresponding benchmark ("BM") annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, maximum drawdowns (defined as the strategies maximum peak-to-trough cumulative loss) and equity tail returns for the 95% and 99% level (defined as the strategies average monthly performance during the worst 5%, respectively the worst 1% of months for the Fama/French global equity market factor) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for a linear regression of the individual momentum strategy returns on its asset class benchmark (the equity benchmark is the Fama/French global market factor, the fixed income benchmark is the Barclays Global Aggregate Bond Index, the commodities benchmark is an equal weighted average of indices for 19 different commodities and the currency benchmark is an equal weighted average of the G11 currencies). Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All returns in this analysis are in USD, after transaction costs and in excess of the risk free rate. All time series are from 31.01.1990 until 31.12.2015 (Source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	Equities		Fixed Income		Commodities		Currencies	
	Mom	BM	Mom	BM	Mom	BM	Mom	BM
Arithmetic Mean p.a.	4.95%	6.50%	0.22%	3.01%	11.14%	0.34%	2.23%	0.96%
t-statistic	*8.08*	*6.22*	*1.01*	*15.62*	*10.89*	*0.40*	*4.59*	*4.59*
Geometric Mean p.a.	4.39%	4.95%	0.14%	2.96%	9.28%	-0.62%	1.89%	0.90%
Volatility p.a.	10.81%	18.44%	3.79%	3.40%	18.07%	14.88%	8.59%	3.69%
Skewness	-0.21	-0.43	-0.36	-0.21	-0.15	-0.29	-0.68	0.14
Kurtosis	4.55	4.26	6.72	3.23	5.64	5.29	4.47	4.14
Autocorrelation	0.05	0.09	-0.00	0.15	-0.02	0.08	0.06	0.11
Equity Tail Return $_{(95\%)}$	0.83%	-11.15%	-0.25%	0.17%	0.09%	-3.07%	0.07%	0.12%
Equity Tail Return $_{(99\%)}$	1.87%	-16.24%	-1.22%	-0.78%	4.09%	-7.75%	0.08%	-0.14%
Max. Drawdown	-19.53%	-56.04%	-17.42%	-8.02%	-42.38%	-55.66%	-21.25%	-11.74%
alpha p.a.	5.61%	-	-0.78%	-	11.12%	-	2.33%	-
t-statistic	*2.76*	-	*-1.02*	-	*2.93*	-	*1.45*	-
beta	-0.10	-	0.34	-	0.07	-	-0.10	-
t-statistic	*-3.00*	-	*4.75*	-	*0.96*	-	*-0.72*	-
Sharpe Ratio	0.46	0.35	0.06	0.88	0.62	0.02	0.26	0.26
Adj. Sharpe Ratio	0.44	0.34	0.06	0.85	0.58	0.02	0.25	0.26

3.4. Volatility

Equity volatility selling is another source of return. Volatility selling using equity index options is an example of selling "lottery tickets" which pay off to the buyer in bad times. This strategy warrants a high-risk premium because large losses coincide with market crashes and the accompanied volatility spikes. In the past, this strategy delivered high Sharpe ratios. However, the high Sharpe ratios may also reflect a peso problem: the absence of a rare and large loss within the data sample (Ilmanen (2011)).

A broad range of empirical analysis dig into the fundamentals of option markets to explain volatility based trading profits. Many studies show that index options, especially index put options, appear to be more expensive than their theoretical Black-Scholes prices, while individual stock options do not appear that expensive. The persistent pattern that equity index options have higher implied volatilities than realized volatilities on average was the fundament for the long term success of equity index volatility selling. The average estimated spread between implied and realized volatility of index options was 2%-4%. (Bakshi, Kapadia and Madan (2003) and Ilmanen (2011)).

The risk based camp of academic literature argues that the different pricing of individual and index options is due to risk factors such as volatility and correlation risk. Particularly present are these risks in index options and in a lower degree in single stock options. For instance, Driessen, Maenhout and Vilkov (2009) argue that index option prices have an embedded correlation risk premium which is absent in single stock options. The authors present a model for the pricing of correlation risk that shows a negative correlation risk premium. Index options, especially index put options, are more expensive because of their ability to hedge correlation risk.

Bakshi and Kapedia (2003) analyze the risk neutral distribution of single stock and index stock returns. They show that the market prices a volatility risk premium in both individual and index options. However, this risk premium is less pronounced in single stock options and the researchers argue that idiosyncratic volatility does not get priced.

The other camp of researchers argues that the perceived expensiveness of index options versus single stock options is due to market inefficiencies. Market supply and demand pressure drives option prices away from their theoretical values. One rationale is that a lot of investors use index put options to hedge their equity exposure against broad market drawdowns and use short call options for covered call strategies on single securities. Hence, market makers adjust their bid ask spreads to balance the excess demand for index put options and the excess supply of single stock call options (Garleanu, Pedersen and Poteshman (2009)).

3.4.1. Methodology of Equity Volatility Selling

Given the economic rationale and empirical evidence, which shows that the gap between implied and realized volatility is largest among equity index options, this thesis focuses on shorting equity index put options as short volatility strategy. The Chicago Board Options Exchange provides the benchmark Index "PUT" which simulates collateralized index put selling on the S&P 500 equity index. Every month a batch of at-the-money index put options are sold. The sold options have expiry dates on a quarterly basis. Hence, on every 3rd month the proceeds from option selling are invested at the three-month treasury bill rate. Any proceeds during intermediary months are invested at the one-month treasury bill rate until the next option expiry date is reached. The number of options sold is determined in such a way that a full collateralization is ensured. At the expiration of the put options, the total value of the treasury bill investments must be equal to the maximum possible loss from final settlement of the options (CBOE (2014)).

3.4.2. Empirical Results of Equity Volatility Selling

Figure 4 shows the wealth evolutions of excess returns of the CBOE PUT index and of the S&P500 index as benchmark and table 4 summarizes performance statistics during the sample period from 01.1990 until 12.2015. The short volatility strategy generated a slightly higher yearly excess return of 6.3% than the S&P 500 but with much less volatility. This results in a relatively high Sharpe ratio of 0.62, whereas the benchmark index has a Sharpe ratio of only 0.46. However, adjusting the Sharpe ratios for higher moments decreases the Sharpe ratio of the volatility selling strategy below the ratio of the benchmark. This is due to the very high kurtosis and negative skewness for the short volatility strategy. The beta of the strategy with the S&P 500 is 0.56 which makes sense since the strategy sells at-the-money put options which have a delta of roughly -0.5. Hence the strategy is not only driven by volatility but also has some directional market exposure.

The empirical results are in line with previous studies and show that a short volatility strategy seems to exchange volatility against tail risk. Moreover, the wealth evolutions and equity tail returns reveal that losses seem to materialize during bad economic conditions in which also the broad market (in this case the S&P 500) incurs large losses. Hence, for evaluating such a strategy it is important to focus not only on the first two moments of the return distribution.

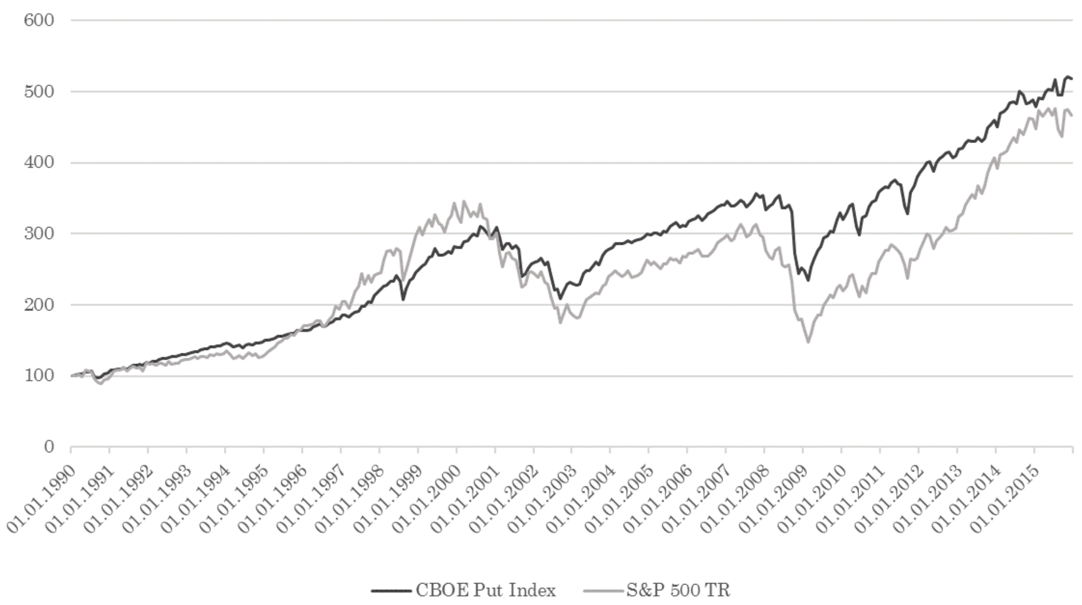

Figure 4: Wealth Evolutions of CBOE Put Index and S&P 500 TR

The Figure shows the wealth evolution of excess returns in USD for the CBOE Put Index and of the S&P 500 Index (total return) from 01.01.1990 until 31.12.2015. Excess returns are calculated by subtracting the 1 month US treasury bill rate from the total return series. (source: Own representation with data from Bloomberg)

Table 4: Summary Statistics of Short Equity Volatility

For the Chicago Board Options Exchange (CBOE) Put Write Index and the S&P 500 total return Index annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, maximum drawdowns (defined as the index's maximum peak-to-trough cumulative loss) and equity tail returns for the 95% and 99% level (defined as the average monthly performance during the worst 5%, respectively the worst 1% of months for the S&P 500 total return Index) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for a linear regression of the CBOE Put Write returns on the S&P 500 total returns. Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All returns in this analysis are in USD and in excess of the risk free rate. All time series are from 31.01.1990 until 31.12.2015 (Source: Own calculations with data from Bloomberg).

	CBOE Put Index	S&P 500 TR
Arithmetic Mean p.a.	6.87%	7.03%
t-statistic	*11.02*	*8.19*
Geometric Mean p.a.	6.33%	5.90%
Volatility p.a.	11.02%	15.18%
Skewness	-1.88	-0.58
Kurtosis	11.98	4.24
Autocorrelation	0.11	0.05
Equity Tail Return $_{(95\%)}$	-7.16%	-9.60%
Equity Tail Return $_{(99\%)}$	-11.67%	-14.35%
Max. Drawdown	-34.17%	-57.29%
alpha p.a.	2.86%	-
t-statistic	*2.63*	-
beta	0.56	-
t-statistic	*25.79*	-
Sharpe Ratio	0.62	0.46
Adj. Sharpe Ratio	0.41	0.44

3.5. Beta

Beta is the traditional and most fundamental source of return, which investors can harvest by investing in a broad market portfolio. The capital asset pricing model (CAPM) introduced among others by Sharpe (1964) postulates, that the market portfolio (a market capitalization weighted portfolio which includes all assets) provides the highest Sharpe ratio. Under the CAPM assumptions, the only risk which is rewarded in equilibrium is the exposure towards systematic risk or in other words towards the broad market.

In this section, the returns which are due to broad market exposure are analyzed. However, the market exposure is split into its sub asset classes like equities, fixed income and commodities[6]. The market returns of the three asset classes served as benchmarks to evaluate the performance of the previously introduced strategies carry, value, momentum and short volatility. The market returns can further be decomposed into the equity risk premium, a bond risk premium, a credit risk premium and an alternative asset premium for commodities (Ilmanen (2011)).

For the market return on equities the Fama/French global market factor is used, for fixed income the Barclays Global Aggregate Bond Index, which includes supranational, government, government related, corporate and securitized bonds and for commodities an equal weighted average of the S&P GSCI Commodity Indices across the same 19 commodities as introduced for the commodities carry strategy (see section 3.1.1).

3.5.1. Empirical Results of Beta Across Asset Classes

Figure 5 shows the wealth evolution of excess returns which are due to broad market exposure towards, equites, fixed income or commodities. Table 5 summarizes performance statistics during the sample period from 01.1990 until

6 As discussed, the market portfolio would include all assets but for consistency reasons, the focus on this thesis is on the asset classes on which specific trading strategies are presented. Currencies as a separate asset class for beta returns are excluded since currencies are a zero-sum game in the long run.

12.2015. Equities and fixed income generated both statistically significant positive excess returns, whereas the arithmetic average return p.a. of commodities is not significantly different from zero. The annualized geometric return of commodities is even negative over the sample period. Equities have the highest excess returns but the volatility of fixed income is much lower than equities. The long run trend of decreasing interest rates induced by central bank interventions was highly beneficial for bonds. Thus, the Sharpe ratio of fixed income is by far the highest among the three asset classes. Moreover, fixed income returns exhibit the lowest tail risk measured by skewness and kurtosis.

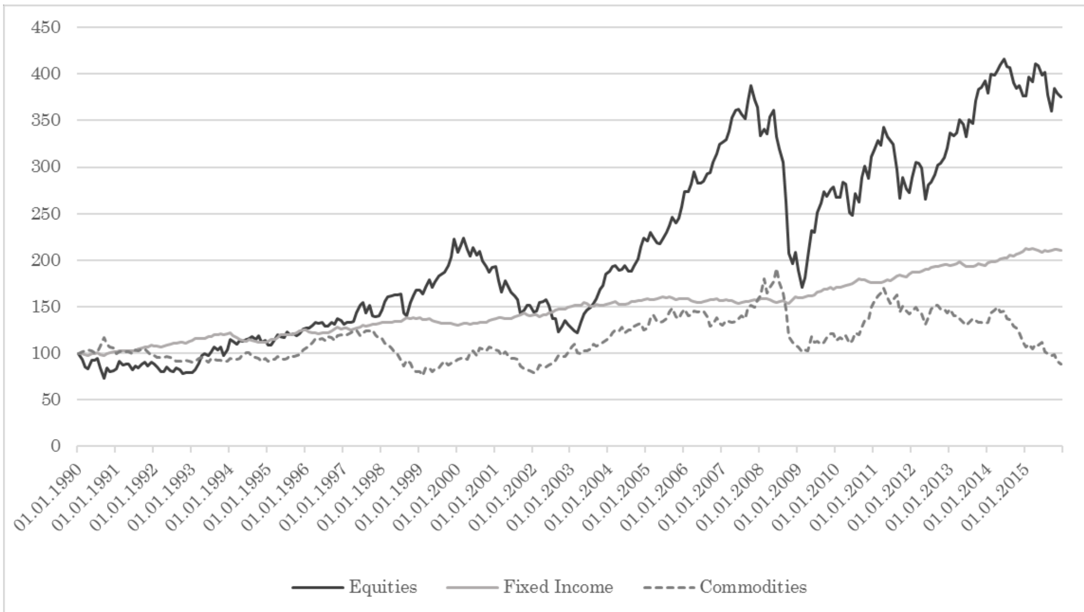

Figure 5: Wealth Evolutions of Beta Across Asset Classes

The Figure shows the wealth evolution of excess returns in USD for global equities, global fixed income and commodities from 01.01.1990 until 31.12.2015. Equities are represented by the Fama/French global equity market factor, fixed income is represented by the excess returns of the Barclays Global Aggregate Bond Index and Commodities are represented by the excess returns on an equal weighted average of S&P GSCI Commodity Indices for 19 different commodities (source: Own calculations with data from Bloomberg and Kenneth French's website).

Table 5: Summary Statistics of Beta Across Asset Classes

For the Fama/French global equity market factor ("Equities"), for the Barclays Global Aggregate Bond Index ("Fixed Income") and for an equal weighted index consisting of 19 different commodities annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, maximum drawdowns (defined as the asset classes maximum peak-to-trough cumulative loss) and equity tail returns for the 95% and 99% level (defined as the average monthly performance during the worst 5%, respectively the worst 1% of months for the Fama/French global market factor) are shown. Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All returns in this analysis are in USD and in excess of the risk free rate. All time series are from 31.01.1990 until 31.12.2015 (source: Own calculations with data from Bloomberg and Kenneth French's website).

	Equities	Fixed Income	Commodities
Arithmetic Mean p.a.	6.50%	3.01%	0.34%
t-statistic	*6.22*	*15.62*	*0.40*
Geometric Mean p.a.	4.95%	2.96%	-0.62%
Volatility p.a.	18.44%	3.40%	14.88%
Skewness	-0.43	-0.21	-0.29
Kurtosis	4.26	3.23	5.29
Autocorrelation	0.09	0.15	0.08
Equity Tail Return $_{(95\%)}$	-11.15%	0.17%	-3.07%
Equity Tail Return $_{(99\%)}$	-16.24%	-0.78%	-7.75%
Max. Drawdown	-56.04%	-8.02%	-55.66%
Sharpe Ratio	0.35	0.88	0.02
Adj. Sharpe Ratio	0.34	0.85	0.02

3.6. Diversified Global Factors

Following Asness, Moskowitz and Pedersen (2013) and Koijen et al. (2015), diversified global return factor portfolios are formed to examine correlations and factor exposures of the various strategy styles among each other. Diversified global return factors mitigate the noise in individual asset class and strategy returns. The global factors are constructed as equal volatility weighted average of the same strategy returns across asset classes. This ensures that the global factors are not mainly driven by the most volatile strategies (for instance the return strategies within commodities exhibit on average the highest volatilities and would dominate the global factors). This methodology is similar to the approach by Asness, Moskowitz and Pedersen (2013) and Koijen et al. (2015) to combine returns from different asset classes and different volatilities.

The weights of the global factors are recalculated at the beginning of each year using historical volatilities up to the end of the preceding year. This procedure ensures that the longest possible time series for volatility estimates are used without inducing a look-ahead bias.

Figure 6 shows wealth evolutions of excess returns of the diversified global carry, value, momentum, short volatility and beta factors[7].

[7] Performance statistics of the global return factors can be found in the appendix.

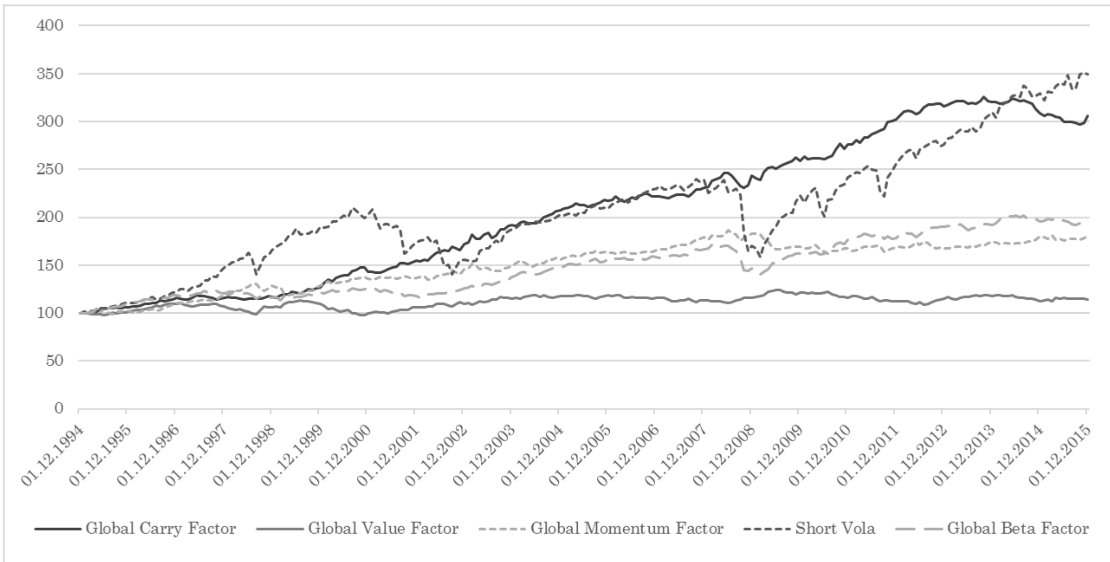

Figure 6: Wealth Evolutions of Global Return Factors

The figure shows wealth evolutions for excess returns of a global carry factor, a global value factor, a global momentum factor, on a short volatility factor and of a global beta factor. The global factors are defined as an equal volatility weighted average of the single factor strategies across equities, fixed income, commodities and currencies (except for the global beta factor which does not include currencies). The short volatility factor is proxied by the CBOE Put Write Index. All returns in this analysis are in USD and in excess of the risk free rate. All time series are from 31.01.1990 until 31.12.2015 (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

Table 6 shows long term correlations among the global carry factors. The numbers show that carry is positively correlated to beta and momentum but negatively correlated to value. Momentum is negatively correlated to value and uncorrelated to beta. Short volatility is positive correlated only to beta, all other correlations with short volatility are low or slightly negative.

Table 6: Correlation Matrix of Global Return Factors

The table shows correlations for excess returns between a global carry factor, a global value factor, a global momentum factor, on a short volatility factor and of a global beta factor. The global factors are defined as an equal volatility weighted average of the single factor strategies across equities, fixed income, commodities and currencies (except for the global beta factor which does not include currencies). The short volatility factor is proxied by the CBOE Put Write Index. The underlying returns in this analysis are in USD and in excess of the risk free rate. The reported correlations use the full time series from 31.01.1990 until 31.12.2015 (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	Carry	Value	Mom.	Short Vola	Beta
Carry	1.00	-0.27	0.25	0.07	0.31
Value		1.00	-0.61	0.08	-0.03
Momentum			1.00	-0.11	-0.02
Short Vola				1.00	0.55
Beta					1.00

Table 7 shows the result of a spanning test in which the global factors are regressed on each other. The global carry, value and momentum factors show positive and statistically significant alphas, suggesting to offer an independent source of return, which cannot be replicated by the other factors. Excluding the beta factor from the regression on the short volatility factor would result in an annualized alpha value of 5.8% and would be statistically significant on the 5% confidence level.

However, the statistical significance of beta coefficients reveals that some factors might be driven by the same underlying economic drivers and only a fraction of the factor returns are independent from each other.

Table 7: Return Factor Exposures to Other Factors

The table shows the coefficients, t-statistics (in italic letters below the coefficients) and R squared for linear regressions of the global factors on all other factors. The global factors are defined as an equal volatility weighted average of the single factor strategies across equities, fixed income, commodities and currencies (except for the global beta factor which does not include currencies). The short volatility factor is proxied by the CBOE Put Write Index. The underlying returns in this analysis are in USD and in excess of the risk free rate. The regression is based on the full time series from 31.01.1990 until 31.12.2015 (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	Carry	Value	Mom.	Short Vola	Beta
alpha p.a.	4,44%	2,75%	2,99%	3,92%	0,11%
	4,94	*3,69*	*3,41*	*1,81*	*0,12*
Carry	-	-0,11	0,14	-0,19	0,31
	-	*-2,05*	*2,25*	*-1,32*	*5,18*
Value	-0,16	-	-0,68	0,10	-0,04
	-2,05	-	*-11,13*	*0,58*	*-0,51*
Momentum	0,15	-0,49	-	-0,13	-0,06
	2,25	*-11,13*	-	*-0,82*	*-0,84*
Short Vola	-0,04	0,01	-0,02	-	0,24
	-1,32	*0,58*	*-0,82*	-	*10,34*
Beta	0,31	-0,03	-0,05	1,28	-
	5,18	*-0,51*	*-0,84*	*10,34*	-
R^2	*0,19*	*0,39*	*0,39*	*0,32*	*0,38*

4. Return Factor Portfolios

4.1. Portfolio Allocation Rules

The starting point of modern portfolio theory was set by Markowitz (1952) with the famous mean variance optimization. This method provides in sample optimal allocations. However, the results out of sample are seriously flawed due to estimation errors of the covariance matrix and the expected returns. Michaud (1989) argues that portfolio optimization is in fact "error maximization" because of the effects of estimation errors on optimal allocations.

Several methods to address these difficulties have been proposed in the literature. Ledoit and Wolf (2003) proposed to shrink the covariance matrix in order to reduce noise in the sample estimate. Fan, Fan and Lv (2008) recommended to reduce the dimensionality of the covariance matrix by using a factor model in combination with a small set of risk factors. Such risk factors should describe expected returns in the cross section sufficiently well. In addition, the estimation error could be significant reduced, if the number of risk factors is smaller than the number of asset classes. However, the definition of a small and meaningful set of risk factors remains challenging.

Some newer portfolio construction techniques focus more on the optimal usage of the estimated risk parameters to overcome the difficulties in expected return estimation. The estimation errors are more present in the expected return vector than in the estimated covariance matrix (Chopra and Ziemba (1993)).

The portfolio construction approaches discussed and analyzed in this thesis are merely long only allocations. Jagannathan and Ma (2003) show that long only constraints have a similar effect to a covariance shrinkage estimator and can lead therefore to more robust allocations.

The following section describes seven different portfolio construction approaches.

4.1.1. Market Capitalization Weighted

Market capitalization weighted portfolios are motivated by the capital asset pricing model (CAPM) which was introduced among others by Sharpe (1964). Under the equilibrium assumptions of the CAPM the market portfolio (a market capitalization weighted portfolio including all assets) coincides with the optimal Sharpe ratio portfolio. As a result, many benchmark indices in today's asset management industry rely on market capitalization weighting schemes. However, holding the market portfolio poses some challenges like non-traded assets. In addition, an extensive literature shows that the prediction of an efficient market portfolio collapses if some of the most relevant assumptions of the CAPM are not met. For instance, if investors have different time horizons, if higher utility is derived from non-traded assets like human capital or social security, under short sale constraints or under other market frictions like taxes (Goltz and Le Sourd (2011)).

4.1.2. Equal Weighted

The equal weighted portfolio (also called 1/n portfolio) is the most straightforward approach and allocates the same weight to each of its components. This simple allocation rule avoids the concentration and procyclical behavior of capitalization weighted portfolios. DeMiguel et. al. (2009) compared the equal weighted portfolio with various other portfolio strategies. The equal weighted portfolio performed better than the mean variance optimization in an out of sample test. Duchin and Levy (2009) argued that out of sample performance depends greatly on the number of assets included in the portfolio. The equal weighted portfolio outperforms when only a small number of asset classes is considered. The equal weighted approach would result in the portfolio with the highest Sharp ratio, provided pairwise correlations, volatilities and expected returns are equal for all assets (Platen and Rendek (2010) and Amenc, Goltz and Martellini (2013)).

4.1.3. Mean Variance Optimization

Introduced by Harry Markowitz (1952), the mean variance optimization balances risk in relation to return on a portfolio level. As return measure, the arithmetic mean return and as risk measure the volatility[8] is used. This optimization model is in line with the economic theory of fully rational investors which maximize their quadratic utility function.

Within the mean variance framework there are two key portfolios, the maximum Sharpe ratio and the global minimum variance portfolio. The maximum Sharpe ratio portfolio coincides with the market portfolio under the CAPM assumptions and as the name suggests, it provides the highest possible Sharpe ratio if the return vector and the covariance matrix is known in advance. Since this is not the case in a real-world example, the input parameters need to be estimated. Due to the high estimation errors in the expected return vector and in the expected covariance matrix, the mean variance optimization leads generally to flawed results in an out of sample test.

The global minimum variance portfolio is the portfolio on the efficient frontier with the lowest variance. Only the covariance matrix must be estimated to calculate the weights of this portfolio. This is a desirable characteristic since estimation errors are more present in the expected return vector than in the estimated covariance matrix (Chopra and Ziemba (1993)).

The global minimum variance portfolio would coincide with the maximum Sharpe ratio portfolio if all expected returns of all asset classes would be equal (Amenc, Goltz and Martellini (2013)).

[8] Volatility is a sufficient risk measure if asset returns are normally distributed or under the assumption of investors with quadratic utility functions. However, volatility as risk measure poses severe limitations if asset returns are not normally distributed and if investors care about higher moments beyond the mean and the variance. As seen in the previous analysis of section 3, many asset and investment strategies exhibit significantly higher kurtosis and a more positive or negative skewness than a normally distributed random variable.

Jagannathan and Ma (2003) showed that the global minimum variance portfolio outperformed an equal weighted portfolio on a risk adjusted basis. However, De Miguel et al. (2009) and Clarke, de Silva and Thorley (2011) argue that the global minimum variance rule leads to highly concentrated portfolios.

4.1.4. Risk Parity and Inverse Volatility Weighting

Qian (2005) and Maillard, Roncalli and Teïletche (2008) describe the risk parity approach (also called equal contribution to risk approach) which focuses on the risk contribution of each asset to the overall risk of the portfolio. The key element of this approach is to understand that risk contributions are not proportional to the dollar quota of an asset in a portfolio. As an example, a historical analysis shows that a portfolio consisting of 60% global equities and 40% global bonds, has a volatility risk contribution from equities which accounts for 92% of total portfolio volatility whereas only 8% of total portfolio volatility is due to the bond allocation[9].

Following Maillard, Roncalli and Teïletche (2008) and Amenc, Goltz and Martellini (2013), the portfolio volatility can be decomposed to obtain an analytical formula for an assets volatility risk contribution. The portfolio volatility σ_P can be decomposed in the following way:

$$\sigma_P = \sqrt{\sum_i w_i^2 \sigma_i^2 + 2 \sum_{i \neq j} w_i \, w_j \; \sigma_{ij}}$$

$$\frac{\partial \sigma_P}{\partial w_i} = \frac{1}{\sigma_P} \left(w_i \sigma_i^2 + \sum_{i \neq j} w_j \, \sigma_{ij} \right)$$

$$\sum_i w_i \; \frac{\partial \sigma_P}{\partial w_i} = \frac{1}{\sigma_P} \; \sum_i w_i \left(w_i \sigma_i^2 + \sum_{i \neq j} w_j \, \sigma_{ij} \right) = \sigma_P$$

[9] The analysis is based on the Fama French global equity market factor and the excess returns on the Barclays global aggregate bond index from 01.1995 until 12.2015. Data is from Bloomberg and darthmouth.tuck.com

Where w_i is the weight of asset i, σ_i the volatility of asset i and σ_{ij} the covariance between asset i and asset j. Hence, the volatility risk contribution c_i of asset i can be written as:

$$c_i = w_i \frac{\partial \sigma_P}{\partial w_i} = \frac{w_i}{\sigma_P} \left(w_i \sigma_i^2 + \sum\nolimits_{i \neq j} w_j \, \sigma_{ij} \right)$$

To obtain better diversified portfolios and to balance the risk exposure across portfolio holdings, Qian (2005) and Maillard, Roncalli and Teïletche (2008) suggest to form portfolios by choosing the weights of each holding in such a way that the risk contribution of each holding is identical. So far no analytical solution has been presented to obtain the risk parity weights of a portfolio and it needs to be solved numerically. However, Clark et al. (2013) presented a semi-analytical solution which relates the asset weights to its betas with the risk parity portfolio.

Maillard, Roncalli and Teïletche (2008) provided a rationale by showing that the risk parity approach coincides with the optimal Sharpe ratio portfolio if all Sharpe ratios and all pairwise correlations across assets are identical.

The Equal Volatility Weighted Portfolio (also called inverse volatility weighting) is a special case of risk parity under the explicit assumption that all pairwise correlations are the same. Under this approach, the portfolio weight of an asset is proportional to the inverse of its volatility Maillard, Roncalli and Teïletche (2008).

4.1.5. Most Diversified Portfolio

Choueifaty and Coignard (2008) proposed and tested the so called most diversified portfolio, which maximizes the diversification ratio, a measure of distance between the over portfolio volatility and the individual volatility of its components. Hence, this approach focuses on an optimal correlation structure within the portfolio to increase diversification. The empirical results showed, that the most diversified portfolio outperformed the market-cap weighted index and an equal weighted portfolio for US and Eurozone equities. The diversification ratio DR is defined as the portfolios weighted average volatility of its holdings relative to the portfolios volatility:

$$DR = \frac{\sum_i w_i \sigma_i}{\sigma_P}$$

Where w_i is the weight of asset i, σ_i is the volatility of asset i and σ_p is the volatility of the portfolio. From the diversification ratio, it can easily be seen, that the most diversified portfolio would coincide with the optimal Sharpe ratio portfolio if all Sharpe ratios of all assets were identical (Choueifaty, Froidure and Reynier (2013)).

4.1.6. Relative Carry

Structuring a portfolio according to the relative carry of its constituents is derived from evolutionary finance findings. This new area of research analyses market behavior and builds models for strategic behavior in financial markets. It is assumed that investment strategies fight for wealth and hence for market share. The central goal is to define an investment strategy which will not be driven out of the market by other strategies and hence "survives" in the market. Survival is guaranteed if and only if the strategy guarantees the fastest asymptotic growth of wealth (Evstigneev, Hens and Schenk-Hoppé (2016)).

In a stochastic model Evstigneev, Hens and Schenk-Hoppé (2016) showed that the survival strategy allocates wealth among the assets in proportion to their fundamental value, in their case to the expected future flow of dividends. Furthermore, the authors specified that the survival strategy is related to the Kelly rule and to the market portfolio defined by the CAPM. The Kelly rule states that best results will be achieved by maximizing the expected logarithm of the portfolio return.

A comparison of the Sharpe ratios derived from diversified global return factors, shows supportive results for the relative carry approach. The global carry factor exhibits the highest Sharpe ratio among all global return factors, suggesting that structuring assets according to relative carry is a superior approach.

4.2. Empirical Analysis of Allocations across Return Factors

4.2.1. Methodology

An empirical analysis is conducted to compare the different portfolio allocation rules and their suitability for portfolios consisting of different return factors. In this thesis, the portfolio allocation rules will focus on long only approaches. Jagannathan and Ma (2003) show that long only constraints have a similar effect to a covariance shrinkage estimator and can lead therefore to more robust allocations.

The following portfolios consisting of various return factors are formed in accordance with the discussed methodologies in section 4.1: equal weighting (EW), inverse volatility weighting (IV), global minimum variance (GMV), maximum Sharpe ratio (MSR), risk parity (RP), most diversified portfolio (MDP) and relative carry[10]. In addition, a portfolio with a traditional allocation across asset classes is formed. Following, Ilmanen and Kizer (2012), the traditional allocation is a proxy

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[10] All portfolio allocation rules except one can easily be implemented as discussed in section 4.1. The only exception is the relative carry allocation. A direct implementation of relative carry would result in a portfolio with an almost exclusive asset allocation in accordance with the commodity carry strategy. This is due to the extremely high carry of many commodity futures (i.e. steep future curve). Koijen et al. (2015) show that a commodity carry strategy creates high returns but only about 1% of the estimated carry of a commodity carry strategy translates into returns. The opposite is the case for equity futures which exhibit a lower carry but the returns of the equity carry strategy exceed the carry estimates (the equity investor earns the dividend yield plus some capital appreciation).

Therefore, a portfolio allocation rule in accordance with relative carry needs to acknowledge the large differences in absolute carry measures across asset classes and the large differences of how the carry estimates are related to future returns. To address this problem, a simple linear regression of carry estimates on future returns is conducted. This regression model is then used to forecast the returns of the next period. This exercise is conducted for every asset class (equities, fixed income, currencies and short volatility) on a yearly rolling basis. If a forecast is produced for the year t, then the full history of asset returns and carry measures up to t-1 is used to estimate the parameters of the regression model. The historical average carry measure up to t-1 is used as input for the return forecasting model. The forecasted returns are then added to the weights of a base portfolio. This procedure creates over and underweight positions relative to the base portfolio. The base portfolio is defined as an equal volatility weighted portfolio across asset classes and strategy styles.

of the global market capitalization weighted portfolio and includes 52.6% global equities, 42.1% global fixed income and 5.3% commodities.

In this context, it is important to note, that the risk factor allocations cover all return sources which are introduced in section 3, however, the traditional portfolio allocation includes only returns due to a passive beta exposure (the Fama/French global market factor, the Barclays global aggregate bond index and an equal weighted commodity index).

Further, only return sources which achieved statistically significant positive average returns would increase Sharpe ratios of the return factor allocations. However, this would introduce a hindsight or selection bias because the returns are not known in advance. The same logic applies to the question whether the broad market returns (beta) in the return factor allocations should be included, since they do not offer a statistically significant positive and independent source of return after controlling for other return factors (see spanning test of section 3.6). Hence, all presented return sources (see section 3) are considered in the allocations to avoid any upward biased results.

The weights of the return factor allocations are recomputed at the end of each year for the following year. During the year, a monthly rebalancing to the defined portfolio weights is assumed.

All allocations are leveraged to an ex ante volatility of 10%.

The input parameters for the various allocation rules (i.e. expected return vector and covariance matrix) are estimated and updated on a yearly basis. They include all information which is available until the point in time on which the new forecast is produced. This ensures, that always the longest possible time window without inducing a hindsight bias is used to estimate parameters. Using longer time windows reduces noise in parameter estimation. However, a fundamental change in market characteristics could make past data less relevant for the future.

The various portfolios are run from 01.1995 until 12.2015. The underlying data for parameter estimation of the different return factors are used starting from 01.1990.

Because of the high turnover of some dynamic strategies - like carry, value or momentum - a comparison between a portfolio consisting of dynamic strategies and a passive portfolio - like the traditional allocation - would be unfair. Hence, a proxy for transaction costs is used. This estimated costs are then subtracted from all dynamic strategy returns (beta returns are not adjusted for transaction costs). Most of the dynamic strategies are based on futures. Locke and Venkatesh (1997) estimate transaction costs in future markets from 0.004% to 0.033%. In this thesis, a conservative estimate for transaction costs of 0.05% and a monthly turnover of 80% is assumed[11].

4.2.2. Empirical Results – 01.1995 until 12.2015

Figure 7 shows wealth evolutions of the risk factor allocations and of the traditional asset class allocation and table 8 shows performance statistics. All risk factor allocations achieved significantly higher returns than the traditional allocation and showed lower absolute drawdowns. All risk factor allocations exhibit large and statistically significant alphas over the traditional allocation. The Sharpe ratios of the risk factor allocations are all close to one. The highest Sharpe ratio was reached by the risk parity allocation (1.06), which is more than double the Sharpe ratio of the traditional allocation (0.43). The highest adjusted Sharpe ratio (adjusted for higher moments) was achieved by the global minimum variance portfolio, followed by the most diversified portfolio. Also, all risk factor allocations show large and statistically significant alfas (significant on the 99% level) over the traditional allocation. In addition, all return factor portfolios - except the relative carry portfolio - show positive and statistically significant alphas over the equal weighted return factor portfolio.

[11]Frazzini, Israel and Moskowitz (2012) estimate that trading costs and especially costs for market impact are much lower for future based trading strategies, but gross returns are higher if the strategies are applied on single stock level.

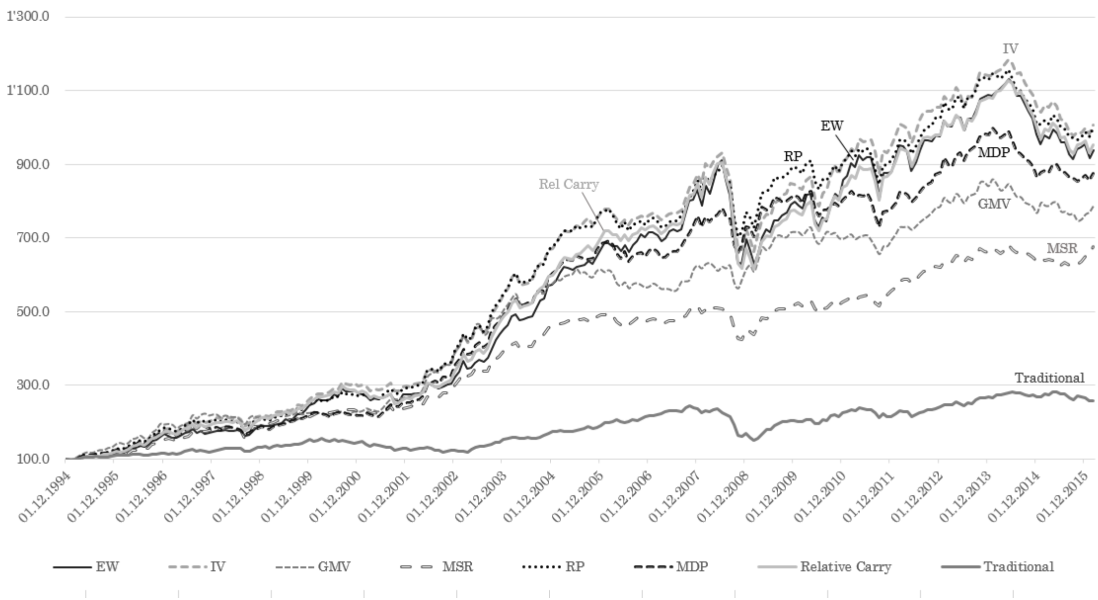

Figure 7: Wealth Evolutions of Strategic Allocations

Wealth evolution starting with USD 100 from 01.1995 until 12.2015 are shown for the different return factor allocations (equal weighted "EW", inverse volatility weighted "IV", global minimum variance "GMV", maximum Sharpe ratio "MSR", risk parity "RP", most diversified portfolio "MDP" and relative carry "Relative Carry") and for a traditional asset class allocation "Traditional" are shown. The underlying return series are based on excess returns, scaled (leveraged) to 10% ex ante annualized volatility and are after transaction costs (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

Table 8: SAA Performance Statistics 01.1995 – 12.2015

For each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and a traditional asset class allocation annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, the percentage of positive months and maximum drawdowns (defined as the strategies maximum peak-to-trough cumulative loss) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All returns in this analysis are in USD, after transaction costs and in excess of the risk free rate. All allocations are scaled (leverage) to 10% annualized ex ante volatility. All time series are from 31.01.1990 until 31.12.2015 (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	12.10%	12.23%	10.65%	9.76%	12.10%	11.38%	12.09%	5.26%
t-statistic	*14.90*	*15.91*	*16.01*	*16.08*	*16.78*	*16.56*	*15.02*	*7.44*
Geometric Mean p.a.	11.34%	11.58%	10.15%	9.32%	11.51%	10.84%	11.39%	4.76%
Volatility p.a.	12.89%	12.20%	10.56%	9.64%	11.44%	10.91%	12.79%	11.23%
Skewness	-0.38	-0.54	0.71	-0.11	-0.07	0.26	-0.74	-0.93
Kurtosis	4.34	5.13	4.51	7.39	4.26	4.08	5.46	6.54
Autocorrelation	0.11	0.14	0.11	0.08	0.12	0.11	0.14	0.16
Positive Months	62.70%	65.87%	60.32%	67.86%	65.48%	63.10%	66.67%	60.32%
Max. Drawdown	-31.17%	-28.93%	-13.05%	-18.06%	-21.39%	-15.44%	-31.99%	-38.99%
Regression on Traditional SAA:								
alpha p.a.	7.34%	8.00%	9.06%	7.19%	8.71%	8.78%	7.43%	-
t-statistic	*3.90*	*4.43*	*4.31*	*4.07*	*4.51*	*4.36*	*4.18*	-
beta	0.85	0.75	0.28	0.46	0.60	0.46	0.83	-
t-statistic	*15.86*	*14.66*	*4.77*	*9.20*	*10.97*	*8.11*	*16.47*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	1.69%	5.11%	2.60%	2.45%	3.08%	0.92%	-
t-statistic	-	*1.96*	*2.76*	*1.98*	*2.37*	*2.28*	*1.22*	-
beta	-	0.86	0.45	0.59	0.79	0.68	0.92	-
t-statistic	-	*42.33*	*10.40*	*19.03*	*32.21*	*21.37*	*51.47*	-
Sharpe Ratio	0.94	1.00	1.01	1.01	1.06	1.04	0.95	0.47
Adj. Sharpe Ratio	0.84	0.82	1.06	0.80	0.98	1.04	0.75	0.42

4.2.3. Empirical Results – Sub-Samples

Splitting the sample period into different market regimes, reveals interesting aspects of the different portfolio allocation rules. As sub-samples the bull really (01.2003 until 11.2007), the great recession (12.2007 until 06.2009) and the monetary easing period (01.2009 until 06.2013) are chosen.

In high performing market phases - like during the bull rally - the traditional asset allocation delivers strong results. Moreover, the traditional asset allocation exhibits the highest adjusted Sharpe ratio, followed by the relative carry and the equal weighted return factor allocations. On the other hand, the relative carry, the equal weighted, the risk parity and the most diversified portfolio exhibit statistically significant alphas over the traditional allocation. However, these alphas might be due to the fact, that these allocations, which consist of various return sources, are driven by other economic factors than those of the traditional allocation.

During bad economic times, the traditional allocation underperforms clearly in absolute terms and on a risk adjusted basis. During the time of the great recession, the global minimum variance, the risk parity and the most diversified portfolio achieved a positive average return.

Generally, a diversification across different return sources beyond beta might be obsolete during good economic times, however, it greatly increases diversification benefits and drawdowns during crisis. This behavior is especially true for more defensive allocation rules - like the global minimum variance, the risk parity and the most diversified portfolio.

Table 9: SAA Performance Statistics during Bull Rally

The table shows performance statistics for each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and for a traditional asset class allocation during the great bull rally from 01.2003 until 11.2007. Annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, the percentage of positive months and maximum drawdowns (defined as the strategies maximum peak-to-trough cumulative loss) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All allocations are scaled (leverage) to 10% annualized ex ante volatility. All returns in this analysis are in USD, after transaction costs and in excess of the risk free rate (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	20.86%	17.54%	9.91%	11.46%	16.82%	16.51%	20.11%	14.63%
t-statistic	*16.05*	*13.03*	*8.02*	*10.25*	*12.46*	*12.23*	*15.42*	*15.00*
Geometric Mean p.a.	20.38%	17.06%	9.46%	11.17%	16.35%	16.03%	19.65%	14.39%
Volatility p.a.	9.98%	10.34%	9.49%	8.59%	10.37%	10.37%	10.02%	7.49%
Skewness	0.10	0.00	0.50	0.31	0.20	0.36	0.06	-0.01
Kurtosis	3.66	3.88	4.42	3.72	3.53	3.61	3.42	2.63
Autocorrelation	0.10	0.12	0.03	0.16	0.13	0.12	0.12	0.15
Positive Months	74.58%	76.27%	64.41%	76.27%	77.97%	71.19%	76.27%	71.19%
Max. Drawdown	-5.60%	-5.48%	-9.75%	-6.68%	-7.69%	-8.30%	-5.08%	-3.48%
Regression on Traditional SAA:								
alpha p.a.	11.45%	7.69%	6.79%	6.97%	9.76%	10.82%	9.51%	-
t-statistic	*2.48*	*1.70*	*1.35*	*1.77*	*2.02*	*2.15*	*2.20*	-
beta	0.60	0.64	0.21	0.30	0.46	0.37	0.68	-
t-statistic	*3.57*	*3.86*	*1.14*	*2.07*	*2.60*	*2.01*	*4.30*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	-1.27%	-2.96%	-1.97%	-1.68%	-1.49%	0.31%	-
t-statistic	-	*-0.62*	*-0.80*	*-0.90*	*-0.81*	*-0.60*	*0.26*	-
beta	-	0.92	0.65	0.67	0.91	0.88	0.95	-
t-statistic	-	*16.44*	*6.37*	*11.18*	*15.84*	*13.02*	*29.17*	-
Sharpe Ratio	2.09	1.70	1.04	1.33	1.62	1.59	2.01	1.95
Adj. Sharpe Ratio	1.91	1.52	1.07	1.36	1.62	1.64	1.91	2.06

Table 10: SAA Performance Statistics during the Great Recession

The table shows performance statistics for each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and for a traditional asset class allocation during the great recession from 12.2007 until 06.2009. Annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, the percentage of positive months and maximum drawdowns (defined as the strategies maximum peak-to-trough cumulative loss) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). Finally, Sharpe Ratios (modified for negative excess returns according to Israelsen (2005)) and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All allocations are scaled (leverage) to 10% annualized ex ante volatility. All returns in this analysis are in USD, after transaction costs and in excess of the risk free rate (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	-4.96%	-4.90%	6.83%	-1.78%	1.55%	5.05%	-7.38%	-14.75%
t-statistic	*-0.81*	*-0.83*	*2.48*	*-0.51*	*0.34*	*1.49*	*-1.20*	*-2.16*
Geometric Mean p.a.	-7.16%	-6.66%	6.22%	-2.49%	0.28%	4.07%	-9.34%	-16.42%
Volatility p.a.	26.83%	25.61%	12.02%	15.29%	19.63%	14.75%	26.90%	29.78%
Skewness	-0.22	-0.55	-0.46	-0.18	-0.48	-0.46	-0.52	-0.39
Kurtosis	2.38	3.14	3.51	3.29	3.28	3.67	2.93	3.44
Autocorrelation	0.21	0.28	0.10	0.23	0.20	0.06	0.27	0.40
Positive Months	47.37%	52.63%	57.89%	42.11%	57.89%	52.63%	47.37%	36.84%
Max. Drawdown	-31.17%	-28.93%	-10.87%	-17.30%	-21.39%	-15.44%	-31.99%	-37.59%
Regression on Traditional SAA:								
alpha p.a.	10.57%	8.91%	12.19%	6.64%	12.75%	13.31%	7.37%	-
t-statistic	*1.10*	*1.06*	*1.52*	*1.16*	*1.53*	*1.47*	*0.90*	-
beta	0.96	0.86	0.31	0.52	0.66	0.48	0.93	-
t-statistic	*7.18*	*7.34*	*2.83*	*6.48*	*5.82*	*3.88*	*8.09*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	-0.60%	8.65%	0.82%	5.25%	8.08%	-2.85%	-
t-statistic	-	*-0.17*	*1.25*	*0.21*	*1.34*	*1.45*	*-1.11*	-
beta	-	0.87	0.34	0.52	0.71	0.56	0.94	-
t-statistic	-	*18.47*	*3.74*	*9.86*	*13.69*	*7.79*	*26.73*	-
Sharpe Ratio	-0.01	-0.01	0.57	-0.00	0.08	0.34	-0.02	-0.04
Adj. Sharpe Ratio	-0.01	-0.01	0.54	-0.00	0.08	0.33	-0.02	-0.04

Table 11: SAA Performance Statistics during Monetary Easing

The table shows performance statistics for each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and for a traditional asset class allocation during the monetary easing period from 01.2009 until 06.2013. Annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, the percentage of positive months and maximum drawdowns (defined as the strategies maximum peak-to-trough cumulative loss) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All allocations are scaled (leverage) to 10% annualized ex ante volatility. All returns in this analysis are in USD, after transaction costs and in excess of the risk free rate (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	8.99%	9.35%	6.09%	8.08%	7.62%	5.32%	9.68%	9.26%
t-statistic	*5.24*	*6.54*	*6.18*	*8.37*	*5.85*	*4.30*	*6.58*	*5.34*
Geometric Mean p.a.	8.17%	8.74%	5.85%	7.85%	7.18%	4.95%	9.07%	8.54%
Volatility p.a.	12.61%	10.50%	7.24%	7.09%	9.58%	9.08%	10.81%	12.74%
Skewness	-0.34	-0.33	0.11	0.14	-0.17	-0.13	-0.36	-0.15
Kurtosis	3.10	3.10	3.10	3.43	3.45	3.52	3.26	2.93
Autocorrelation	0.02	-0.02	0.08	0.06	0.05	0.07	0.01	0.09
Positive Months	57.41%	61.11%	62.96%	66.67%	61.11%	61.11%	64.81%	57.41%
Max. Drawdown	-12.66%	-9.79%	-9.86%	-6.02%	-10.28%	-11.63%	-10.18%	-11.74%
Regression on Traditional SAA:								
alpha p.a.	0.18%	1.71%	2.90%	4.06%	1.60%	0.56%	2.01%	-
t-statistic	*0.07*	*0.74*	*1.08*	*1.83*	*0.64*	*0.19*	*0.85*	-
beta	0.95	0.82	0.34	0.43	0.65	0.52	0.82	-
t-statistic	*14.67*	*14.58*	*5.34*	*8.07*	*10.68*	*7.43*	*14.42*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	1.81%	2.70%	3.74%	1.31%	0.01%	1.94%	-
t-statistic	-	*1.33*	*1.13*	*2.37*	*0.93*	*0.00*	*2.15*	-
beta	-	0.83	0.38	0.48	0.70	0.60	0.85	-
t-statistic	-	*26.63*	*6.88*	*13.30*	*21.70*	*13.04*	*41.36*	-
Sharpe Ratio	0.71	0.89	0.84	1.14	0.80	0.59	0.90	0.73
Adj. Sharpe Ratio	0.68	0.84	0.85	1.14	0.77	0.57	0.84	0.71

4.2.4. Macroeconomic Sensitivities

So far, the focus was on returns and different sources of returns but not on macroeconomic risk exposures. However, investors might be concerned about macroeconomic shocks and their influence on investments. Following the approach of Ilmanen, Maloney and Ross (2014), the impact of three key macroeconomic variables on the different return factor allocations and on the traditional asset class allocation is analyzed. Economic growth, changes in the real interest rate and unexpected inflation are taken as key macroeconomic indicators. All three indicators are based on standardized values (z-scores). For growth, the US purchasing manager index is used, for real rates, the changes in the US 2-year real rate and for unexpected inflation the difference between actual inflation and expected inflation is used. The actual inflation rate is based on the core CPI for the US (consumer price index) and expected inflation is measured by the US inflation forecast from the University of Chicago. Figure 8 shows the macroeconomic indicators over the relevant time period.

Figure 9 shows Sharpe ratios[12] of the different risk factor allocations and for the traditional asset allocation. In general, the strategic allocation which are diversified across many return factors show much less variation in Sharpe ratios across the different macroeconomic regimes than the traditional allocation which is diversified across asset classes only. The traditional allocation clearly performs better in an environment of high growth, increasing real rates and low unexpected inflation. These are all scenarios in which equities perform well.

The global minimum variance portfolio exhibits the highest variation in Sharpe ratios across macro scenarios. This strategy performs particular well during crisis, but has a significant worse Sharpe ratio during rising real yields. This is explained by the high fixed income allocation of this portfolio. Whereas the relative carry allocation shows a pro-cyclical behavior across macroeconomic regimes, the most

[12] Detailed performance statistics across macroeconomic scenarios are shown in the appendix "Macroeconomic Sensitivities".

diversified portfolio and the global minimum variance portfolio show an anti-cyclical behavior.

The lowest variation in Sharpe ratios is shown by the risk parity portfolio. This portfolio seems to be very robust and well diversified across macroeconomic shocks.

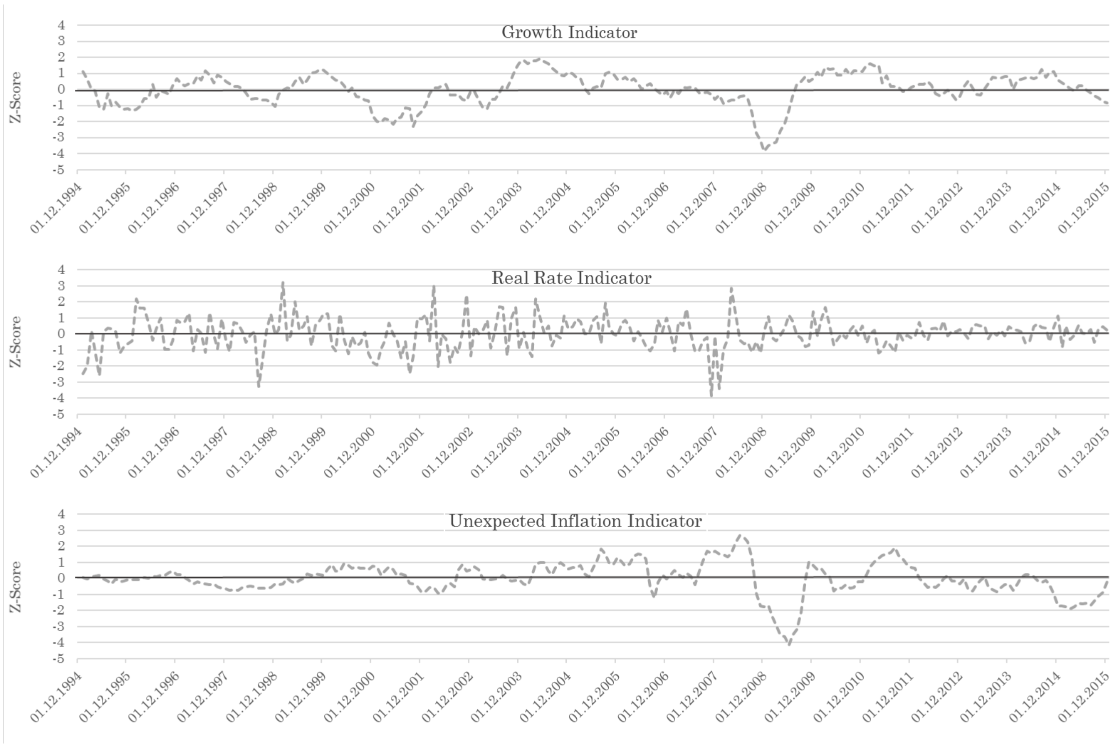

Figure 8: Macroeconomic Indicators

The figure shows z-scores for three macroeconomic indicators: growth, change in the US 2-year real interest rate and unexpected inflation. (Source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR, Kenneth French's website and the federal reserve bank of St. Louis).

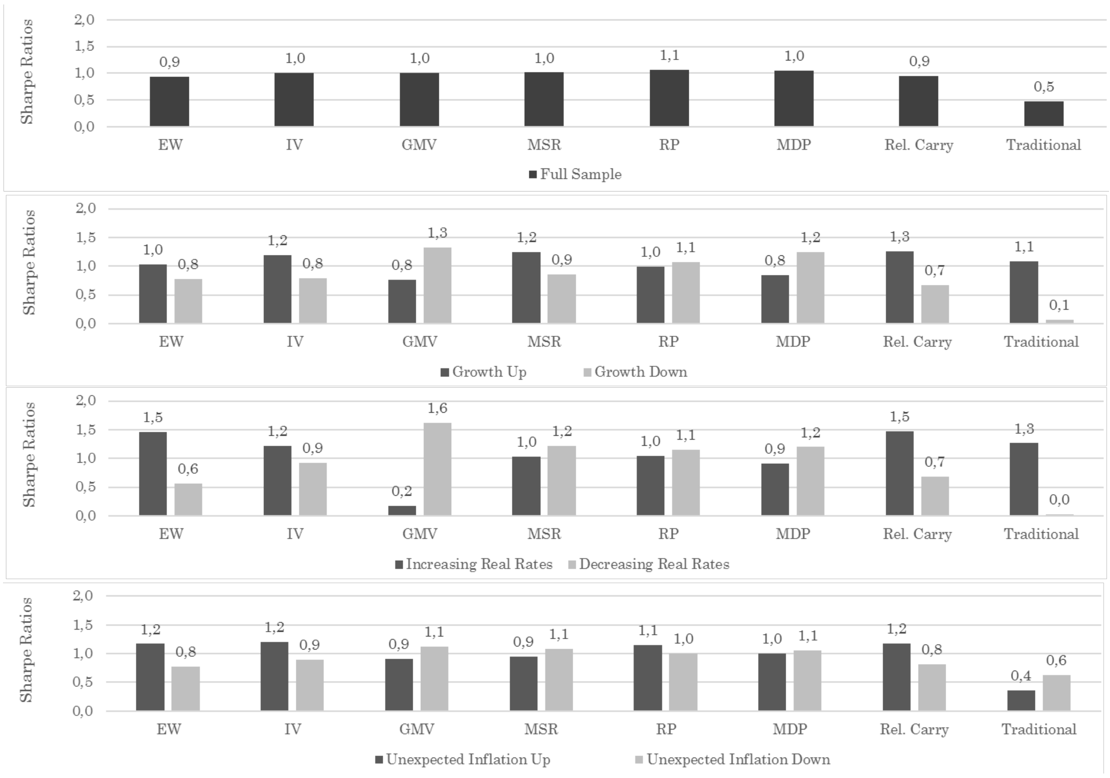

Figure 9: Sharpe Ratios across Macroeconomic Scenarios

The figure shows Sharpe ratios for each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and for a traditional asset class allocation for the full sample period from 01.1995 – 12.2015 and during 6 different macroeconomic scenarios. The scenarios are defined as growth, change in the US 2-year real interest rate and unexpected inflation. (Source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR, Kenneth French's website and the federal reserve bank of St. Louis).

5. Challenges and Implementation Issues

Compared to the traditional asset allocation, risk factor allocations may raise additional implementation problems. For instance, many investors are reluctant to use leverage, derivatives and short selling. Other critical aspects are increased complexity and high turnover.

In addition, there is the fundamental question: will these results still be valid in the future or are they only sample specific? A fundamental back testing problem is hindsight. The empirical analysis was based on an out-of-sample test. Expected returns and co-variances where not known in advance. However, it is very difficult to create a true out-of-sample testing environment. Due to the research from previous studies, it was known in advance, that strategies like carry, value, momentum, and short volatility produced good results in the past. Hence, it is very important that the return factors are based on a sound economic rationale. This can help mitigate random patterns in the data which just appear to be significant but are due to overfitting.

Market impact costs have not been considered yet. They depend greatly on the instruments, number and wealth of investors applying a specific strategy. Market impact costs depend also on investors' short term views: are they exploiting a market inefficiency or harvesting returns against a higher risk exposure.

6. Conclusion

A Comprehensive review of existing research and an empirical analysis using available market data over a 20-year period starting in 01.1995 until 12.2015 leads to the conclusion that strategic allocations defined directly across various return sources have several advantages over a traditional allocation across asset classes. The inclusion of various return sources beyond beta increases Sharpe ratios, lowers drawdowns and leads to allocations which are better diversified across macroeconomic shocks.

The portfolio construction approaches do not show dramatically different Sharpe ratios in the long run. However, comparing the Sharpe ratios during different economic environments shows significant variations. The lowest variation was found for the risk parity portfolio.

The asset management industry would be well advised to consider returns beyond beta, given the strong results of return factor allocations. However, the strategies discussed in this thesis are complex to implement and supervise. In addition, the use of leverage, derivatives and short positions is not suitable for many investors.

Politically driven economic parameters (such as quantitative easing and negative interest rates over a long period) may lead to different results. In the academic literature exist little consensus regarding which return factors should be considered and whether they will continue to be profitable in the future. Further research on this topic might be needed before strategic allocations across return factors can be considered for the broad investment audience.

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8. Appendix I: Performance Statistics Global Factors

Table 12: Performance Statistics Global Return Factors

For each global return factor annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilitiy (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, maximum drawdowns (defined as the factors maximum peak-to-trough cumulative loss) are shown. The global factors are defined as an equal volatility weighted average of the single factor strategies across equities, fixed income, commodities and currencies (except for the global beta factor which does not include currencies). The short volatility factor is proxied by the CBOE Put Write Index. The underlying returns in this analysis are in USD and in excess of the risk free rate. All underlying time series are from 31.01.1990 until 31.12.2015 (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	Carry Factor	Value Factor	Mom. Factor	Short Vola Factor	Beta Factor
Arithmetic Mean p.a.	5.56%	0.71%	2.94%	6.75%	3.22%
t-statistic	*20.59*	*2.64*	*9.68*	*9.04*	*9.93*
Geometric Mean p.a.	5.46%	0.63%	2.83%	6.13%	3.10%
Volatility p.a.	4.29%	4.25%	4.82%	11.86%	5.14%
Skewness	0.34	0.23	-0.55	-1.82	-1.04
Kurtosis	4.08	3.94	4.03	11.12	7.66
Autocorrelation	0.03	0.08	0.04	0.12	0.08
Positive Months	65.48%	49.60%	62.70%	72.62%	63.10%
Max. Drawdown	-8.89%	-13.65%	-13.18%	-34.17%	-18.01%
Sharpe Ratio	1.30	0.17	0.61	0.57	0.63
Adj. Sharpe Ratio	1.29	0.17	0.57	0.41	0.51

9. Appendix II: Unlevered Allocations

Table 13: SAA Unlevered Performance Statistics before Costs

For each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and a traditional asset class allocation annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, the percentage of positive months and maximum drawdowns (defined as the strategies maximum peak-to-trough cumulative loss) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All returns in this analysis are in USD, before transaction costs and in excess of the risk free rate. Estimation period is from 31.01.1990 until 31.12.2015 (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	4.03%	3.29%	2.49%	3.26%	2.98%	2.85%	3.66%	5.17%
t-statistic	*18.76*	*21.88*	*25.31*	*22.76*	*24.04*	*24.29*	*19.80*	*8.00*
Geometric Mean p.a.	3.98%	3.26%	2.48%	3.23%	2.96%	2.84%	3.62%	4.74%
Volatility p.a.	3.41%	2.38%	1.56%	2.27%	1.97%	1.86%	2.93%	10.26%
Skewness	-0.40	-0.53	0.65	-0.10	-0.09	0.23	-0.71	-0.76
Kurtosis	4.17	4.82	4.42	7.14	4.13	3.98	5.12	5.46
Autocorrelation	0.10	0.13	0.10	0.08	0.12	0.11	0.13	0.14
Positive Months	67.86%	70.24%	69.44%	71.83%	71.03%	68.65%	70.24%	60.32%
Max. Drawdown	-8.33%	-5.58%	-1.37%	-4.19%	-3.56%	-2.41%	-7.49%	-34.82%
Regression on Traditionl SAA:								
alpha p.a.	2.74%	2.45%	2.25%	2.65%	2.39%	2.40%	2.57%	-
t-statistic	*5.68*	*7.13*	*7.40*	*6.48*	*7.44*	*7.20*	*6.50*	-
beta	0.25	0.16	0.05	0.12	0.11	0.09	0.21	-
t-statistic	*16.47*	*15.13*	*4.95*	*9.14*	*11.27*	*8.36*	*17.05*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	0.71%	1.48%	1.18%	0.93%	1.11%	0.44%	-
t-statistic	-	*4.10*	*5.30*	*3.66*	*5.06*	*4.67*	*2.53*	-
beta	-	0.64	0.25	0.51	0.51	0.43	0.80	-
t-statistic	-	*42.41*	*10.33*	*18.29*	*31.62*	*21.01*	*52.96*	-
Sharpe Ratio	1.18	1.38	1.59	1.43	1.51	1.53	1.25	0.50
Adj. Sharpe Ratio	1.01	1.01	1.63	0.89	1.32	1.47	0.89	0.46

Table 14: SAA Unlevered Performance Statistics after Costs

For each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and a traditional asset class allocation annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, the percentage of positive months and maximum drawdowns (defined as the strategies maximum peak-to-trough cumulative loss) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All returns in this analysis are in USD, after transaction costs and in excess of the risk free rate. Estimation period is from 31.01.1990 until 31.12.2015 (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	3.04%	2.30%	1.51%	2.28%	2.00%	1.87%	2.67%	5.17%
t-statistic	*14.15*	*15.32*	*15.37*	*15.89*	*16.12*	*15.94*	*14.46*	*8.00*
Geometric Mean p.a.	2.99%	2.28%	1.50%	2.25%	1.98%	1.86%	2.63%	4.74%
Volatility p.a.	3.41%	2.38%	1.56%	2.27%	1.97%	1.86%	2.93%	10.26%
Skewness	-0.40	-0.53	0.65	-0.10	-0.09	0.23	-0.71	-0.76
Kurtosis	4.17	4.82	4.42	7.14	4.13	3.98	5.12	5.46
Autocorrelation	0.10	0.13	0.10	0.08	0.12	0.11	0.13	0.14
Positive Months	62.70%	65.87%	60.32%	67.86%	65.48%	63.10%	66.67%	60.32%
Max. Drawdown	-8.93%	-6.13%	-2.02%	-4.34%	-3.87%	-2.72%	-8.09%	-34.82%
Regression on Traditionl SAA:								
alpha p.a.	1.76%	1.47%	1.27%	1.67%	1.42%	1.43%	1.59%	-
t-statistic	*3.66*	*4.30*	*4.21*	*4.11*	*4.43*	*4.29*	*4.04*	-
beta	0.25	0.16	0.05	0.12	0.11	0.09	0.21	-
t-statistic	*16.47*	*15.13*	*4.95*	*9.14*	*11.27*	*8.36*	*17.05*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	0.36%	0.75%	0.71%	0.46%	0.56%	0.24%	-
t-statistic	-	*2.15*	*2.78*	*2.27*	*2.56*	*2.42*	*1.45*	-
beta	-	0.64	0.25	0.51	0.51	0.43	0.80	-
t-statistic	-	*42.41*	*10.33*	*18.29*	*31.62*	*21.01*	*52.96*	-
Sharpe Ratio	0.89	0.97	0.97	1.00	1.02	1.00	0.91	0.50
Adj. Sharpe Ratio	0.80	0.81	1.02	0.81	0.95	1.00	0.75	0.46

10. Appendix III: Levered Allocations before Costs

Table 15: SAA Performance Statistics Levered before Costs

For each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and a traditional asset class allocation annualized arithmetic mean returns (including t-statistics), annualized geometric mean returns, annualized volatilities (adjusted for first order autocorrelation) and skewness kurtosis and first order autocorrelation of monthly returns are reported. Furthermore, the percentage of positive months and maximum drawdowns (defined as the strategies maximum peak-to-trough cumulative loss) are shown. In addition, regression coefficients and their corresponding t-statistics are reported for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). Finally, Sharpe Ratios and adjusted Sharp Ratios which are penalized for negative skewness and excess kurtosis are reported. All allocations are scaled (leverage) to 10% ex ante annualized volatility. All returns in this analysis are in USD, after transaction costs and in excess of the risk free rate. Estimation period is from 31.01.1990 until 31.12.2015 (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	16.13%	17.69%	17.85%	14.26%	18.37%	17.69%	16.73%	5.26%
t-statistic	*19.83*	*22.98*	*26.75*	*23.53*	*25.45*	*25.74*	*20.74*	*7.44*
Geometric Mean p.a.	15.35%	17.01%	17.32%	13.80%	17.75%	17.13%	16.00%	4.76%
Volatility p.a.	12.91%	12.22%	10.59%	9.62%	11.46%	10.91%	12.81%	11.23%
Skewness	-0.38	-0.53	0.71	-0.11	-0.06	0.26	-0.73	-0.93
Kurtosis	4.33	5.11	4.51	7.40	4.25	4.09	5.44	6.54
Autocorrelation	0.11	0.14	0.11	0.08	0.12	0.11	0.14	0.16
Positive Months	67.86%	70.24%	69.44%	71.83%	71.03%	68.65%	70.24%	60.32%
Max. Drawdown	-29.77%	-27.06%	-8.86%	-17.43%	-19.80%	-13.76%	-30.26%	-38.99%
Regression on Traditionl SAA:								
alpha p.a.	11.22%	13.28%	16.17%	11.60%	14.82%	14.96%	11.90%	-
t-statistic	*5.86*	*7.17*	*7.45*	*6.44*	*7.46*	*7.23*	*6.56*	-
beta	0.85	0.75	0.28	0.46	0.60	0.46	0.83	-
t-statistic	*15.82*	*14.62*	*4.75*	*9.20*	*10.95*	*8.09*	*16.42*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	3.44%	10.21%	4.62%	5.24%	6.36%	1.74%	-
t-statistic	-	*3.86*	*5.24*	*3.39*	*4.86*	*4.52*	*2.25*	-
beta	-	0.86	0.45	0.59	0.79	0.68	0.92	-
t-statistic	-	*42.37*	*10.39*	*19.01*	*32.23*	*21.38*	*51.49*	-
Sharpe Ratio	1.25	1.45	1.69	1.48	1.60	1.62	1.31	0.47
Adj. Sharpe Ratio	1.04	0.99	1.72	0.84	1.36	1.54	0.87	0.42

11. Appendix IV: Macroeconomic Sensitivities

Table 16: Performance Statistics during high Growth Scenarios

For each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and a traditional asset class allocation performance statistics during "high growth periods" are reported (these periods are defined as the months in which the standardized US PMI is above its long run mean). Annualized arithmetic mean returns (including t-statistics), annualized volatilities are reported. In addition, regression coefficients and their corresponding t-statistics are shown for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). All returns in this analysis correspond to the returns of the original allocations (from 01.1995 – 12.2015) which are scaled (leverage) to 10% ex ante annualized volatility, in USD, after transaction costs and in excess of the risk free rate. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	12,04%	12,38%	7,22%	9,24%	10,35%	9,05%	12,95%	8,69%
t-statistic	*12,26*	*14,17*	*9,11*	*14,76*	*11,75*	*10,04*	*15,04*	*12,86*
Volatility p.a.	11,71%	10,41%	9,45%	7,46%	10,49%	10,75%	10,27%	8,05%
Positive Months	64,79%	66,90%	56,34%	69,01%	63,38%	61,27%	66,90%	63,38%
Regression on Traditional SAA:								
alpha p.a.	9,29%	9,11%	13,58%	8,38%	12,37%	13,86%	7,54%	-
t-statistic	*3,43*	*3,52*	*4,26*	*3,06*	*4,20*	*4,25*	*3,19*	-
beta	0,80	0,71	0,20	0,41	0,51	0,32	0,82	-
t-statistic	*10,73*	*10,02*	*3,13*	*6,57*	*7,57*	*5,12*	*11,45*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	0,99%	9,87%	3,28%	5,33%	8,10%	-1,11%	-
t-statistic	-	*0,84*	*3,19*	*1,13*	*2,76*	*3,05*	*-0,40*	-
beta	-	0,87	0,38	0,54	0,73	0,59	0,94	-
t-statistic	-	*28,83*	*6,78*	*12,50*	*21,86*	*14,40*	*33,22*	-
Sharpe Ratio	1,03	1,19	0,76	1,24	0,99	0,84	1,26	1,08

Table 17: Performance Statistics during low Growth Scenarios

For each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and a traditional asset class allocation performance statistics during "low growth periods" are reported (these periods are defined as the months in which the standardized US PMI is below its long run mean). Annualized arithmetic mean returns (including t-statistics), annualized volatilities are reported. In addition, regression coefficients and their corresponding t-statistics are shown for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). All returns in this analysis correspond to the returns of the original allocations (from 01.1995 – 12.2015) which are scaled (leverage) to 10% ex ante annualized volatility, in USD, after transaction costs and in excess of the risk free rate. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	12,17%	12,04%	15,21%	10,44%	14,39%	14,44%	10,99%	0,99%
t-statistic	*8,15*	*8,26*	*13,84*	*9,04*	*11,29*	*13,00*	*6,99*	*0,70*
Volatility p.a.	15,65%	15,28%	11,53%	12,11%	13,38%	11,65%	16,49%	14,85%
Positive Months	60,00%	64,55%	65,45%	66,36%	68,18%	65,45%	66,36%	56,36%
Regression on Traditional SAA:								
alpha p.a.	9,19%	8,39%	11,63%	8,44%	11,08%	12,01%	7,43%	-
t-statistic	*3,43*	*3,52*	*4,26*	*3,06*	*4,20*	*4,25*	*3,19*	-
beta	0,83	0,74	0,21	0,49	0,56	0,37	0,85	-
t-statistic	*10,73*	*10,02*	*3,13*	*6,57*	*7,57*	*5,12*	*11,45*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	0,36%	7,95%	2,66%	3,98%	6,24%	-1,23%	-
t-statistic	-	*0,84*	*3,19*	*1,13*	*2,76*	*3,05*	*-0,40*	-
beta	-	0,88	0,39	0,62	0,75	0,61	0,95	-
t-statistic	-	*28,83*	*6,78*	*12,50*	*21,86*	*14,40*	*33,22*	-
Sharpe Ratio	0,78	0,79	1,32	0,86	1,08	1,24	0,67	0,07

Table 18: Performance Statistics during rising Real Yields

For each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and a traditional asset class allocation performance statistics during "rising real yields" are reported (these periods are defined as the months in which the US 2-year real yield is increasing). Annualized arithmetic mean returns (including t-statistics), annualized volatilities are reported. In addition, regression coefficients and their corresponding t-statistics are shown for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). All returns in this analysis correspond to the returns of the original allocations (from 01.1995 – 12.2015) which are scaled (leverage) to 10% ex ante annualized volatility, in USD, after transaction costs and in excess of the risk free rate. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	15,49%	10,53%	1,36%	7,51%	9,43%	8,22%	13,29%	9,87%
t-statistic	*16,88*	*14,09*	*1,97*	*11,94*	*12,00*	*10,56*	*17,02*	*14,60*
Volatility p.a.	10,58%	8,62%	7,94%	7,25%	9,07%	8,98%	9,01%	7,80%
Positive Months	65,41%	65,41%	50,38%	66,92%	63,91%	62,41%	68,42%	64,66%
Regression on Traditional SAA:								
alpha p.a.	8,10%	13,84%	21,80%	12,12%	14,90%	14,82%	10,43%	-
t-statistic	*0,28*	*1,18*	*13,82*	*1,21*	*1,04*	*0,46*	*0,77*	-
beta	0,90	0,87	0,39	0,59	0,69	0,51	0,96	-
t-statistic	*1,12*	*1,14*	*5,42*	*1,29*	*1,28*	*0,90*	*1,34*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	5,96%	16,83%	6,47%	7,62%	8,60%	2,37%	-
t-statistic	-	*4,30*	*5,73*	*2,03*	*2,09*	*0,39*	*1,69*	-
beta	-	0,93	0,54	0,67	0,84	0,71	0,98	-
t-statistic	-	*8,55*	*1,85*	*3,70*	*4,85*	*2,19*	*6,14*	-
Sharpe Ratio	1,46	1,22	0,17	1,04	1,04	0,92	1,48	1,27

Table 19: Performance Statistics during falling Real Yields

For each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and a traditional asset class allocation performance statistics during "falling real yields" are reported (these periods are defined as the months in which the US 2-year real yield is decreasing). Annualized arithmetic mean returns (including t-statistics), annualized volatilities are reported. In addition, regression coefficients and their corresponding t-statistics are shown for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). All returns in this analysis correspond to the returns of the original allocations (from 01.1995 – 12.2015) which are scaled (leverage) to 10% ex ante annualized volatility, in USD, after transaction costs and in excess of the risk free rate. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	8,41%	14,16%	21,95%	12,33%	15,15%	15,01%	10,77%	0,32%
t-statistic	*6,14*	*10,05*	*17,70*	*13,29*	*12,51*	*13,08*	*7,40*	*0,25*
Volatility p.a.	14,96%	15,37%	13,53%	10,13%	13,21%	12,51%	15,89%	14,25%
Positive Months	59,66%	66,39%	71,43%	68,91%	67,23%	63,87%	64,71%	55,46%
Regression on Traditional SAA:								
alpha p.a.	8,10%	13,84%	21,80%	12,12%	14,90%	14,82%	10,43%	-
t-statistic	*0,07*	*0,59*	*8,59*	*0,90*	*0,72*	*0,57*	*0,29*	-
beta	0,90	0,87	0,39	0,59	0,69	0,51	0,96	-
t-statistic	*0,81*	*0,87*	*3,83*	*0,95*	*0,92*	*0,73*	*1,06*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	5,96%	16,83%	6,47%	7,62%	8,60%	2,37%	-
t-statistic	-	*10,26*	*3,82*	*7,75*	*7,76*	*8,57*	*1,26*	-
beta	-	0,93	0,54	0,67	0,84	0,71	0,98	-
t-statistic	-	*25,69*	*1,35*	*12,40*	*15,67*	*21,38*	*7,29*	-
Sharpe Ratio	0,56	0,92	1,62	1,22	1,15	1,20	0,68	0,02

Table 20: Performance Statistics during high Unexpected Inflation

For each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and a traditional asset class allocation performance statistics during times of "high unexpected inflation" are reported (these periods are defined as the months in which the standardized US surprise inflation is above its long term mean. The US surprise inflation is the difference between the US inflation forecast of the university of Michigan and the realized inflation rate). Annualized arithmetic mean returns (including t-statistics), annualized volatilities are reported. In addition, regression coefficients and their corresponding t-statistics are shown for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). All returns in this analysis correspond to the returns of the original allocations (from 01.1995 – 12.2015) which are scaled (leverage) to 10% ex ante annualized volatility, in USD, after transaction costs and in excess of the risk free rate. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR, federal reserve bank of St. Louis "FRED" and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	14,13%	13,74%	10,22%	8,77%	13,04%	11,64%	13,73%	3,24%
t-statistic	*13,12*	*13,43*	*10,19*	*10,64*	*12,83*	*11,18*	*13,22*	*4,03*
Volatility p.a.	12,09%	11,48%	11,26%	9,25%	11,41%	11,69%	11,66%	9,04%
Positive Months	67,46%	68,25%	61,90%	71,43%	68,25%	64,29%	69,84%	59,52%
Regression on Traditional SAA:								
alpha p.a.	18,91%	23,82%	22,09%	18,76%	21,82%	19,55%	20,72%	-
t-statistic	*2,16*	*3,30*	*3,20*	*2,98*	*3,04*	*2,79*	*2,55*	-
beta	0,84	0,78	0,74	0,32	0,89	0,94	0,71	-
t-statistic	*2,57*	*3,35*	*4,37*	*2,43*	*3,95*	*4,43*	*2,55*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	6,55%	11,31%	4,44%	6,39%	8,31%	2,58%	-
t-statistic	-	*2,42*	*1,44*	*1,70*	*1,43*	*0,96*	*1,33*	-
beta	-	0,89	0,67	0,60	0,89	0,78	0,90	-
t-statistic	-	*10,77*	*3,70*	*5,67*	*8,32*	*5,41*	*13,33*	-
Sharpe Ratio	1,17	1,20	0,91	0,95	1,14	1,00	1,18	0,36

Table 21: Performance Statistics during low Unexpected Inflation

For each return factor allocation (equal weighted, inverse volatility weighted, global minimum variance, maximum Sharpe ratio, risk parity, most diversified portfolio and relative carry) and a traditional asset class allocation performance statistics during times of "low unexpected inflation" are reported (these periods are defined as the months in which the standardized US surprise inflation is below its long term mean. The US surprise inflation is the difference between the US inflation forecast of the university of Michigan and the realized inflation rate). Annualized arithmetic mean returns (including t-statistics), annualized volatilities are reported. In addition, regression coefficients and their corresponding t-statistics are shown for two linear regressions (1st regression: return factor portfolios on the traditional asset class allocation, 2nd regression: return factor allocations on equal weighted return factor allocation). All returns in this analysis correspond to the returns of the original allocations (from 01.1995 – 12.2015) which are scaled (leverage) to 10% ex ante annualized volatility, in USD, after transaction costs and in excess of the risk free rate. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR, federal reserve bank of St. Louis "FRED" and Kenneth French's website).

	EW	IV	GMV	MSR	RP	MDP	Rel. Carry	Traditional
Arithmetic Mean p.a.	10,10%	10,73%	11,07%	10,76%	11,16%	11,11%	10,48%	7,32%
t-statistic	*8,68*	*10,07*	*12,57*	*12,10*	*11,17*	*11,87*	*9,12*	*7,10*
Volatility p.a.	13,05%	11,97%	9,88%	9,98%	11,21%	10,51%	12,90%	11,59%
Positive Months	57,94%	63,49%	58,73%	64,29%	62,70%	61,90%	63,49%	61,11%
Regression on Traditional SAA:								
alpha p.a.	3,52%	4,63%	8,55%	6,66%	6,26%	7,46%	3,80%	-
t-statistic	*1,97*	*2,64*	*2,53*	*1,90*	*2,48*	*2,45*	*2,18*	-
beta	0,87	0,80	0,33	0,53	0,64	0,47	0,89	-
t-statistic	*6,53*	*7,12*	*2,97*	*5,42*	*5,80*	*4,76*	*7,70*	-
Regression on EW Return Factor SAA:								
alpha p.a.	-	1,95%	6,75%	4,35%	3,20%	4,44%	0,90%	-
t-statistic	-	*1,73*	*1,90*	*0,96*	*1,48*	*1,43*	*0,95*	-
beta	-	0,86	0,41	0,62	0,77	0,65	0,94	-
t-statistic	-	*15,62*	*4,28*	*8,04*	*13,82*	*11,00*	*17,29*	-
Sharpe Ratio	0,77	0,90	1,12	1,08	1,00	1,06	0,81	0,63

12. Appendix V: Correlation Matrix All Return Factors

Table 22: Correlation Matrix All Return Factors 01.1990 – 12.2015

The table shows the correlations of the return factors across asset classes. The estimation period is from 01.1990 until 12.2015. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

		Carry				Value				Momentum				S. Vola	Beta		
		EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	FI	Com	FX	PUT	EQ	FI	Com
Carry	Equities	1.00	0.08	-0.03	0.05	0.17	-0.02	-0.03	0.00	-0.02	0.04	-0.03	-0.05	0.04	-0.01	-0.03	0.05
	Fixed Income		1.00	0.03	0.05	-0.08	-0.25	-0.03	-0.12	0.09	0.36	0.04	0.05	-0.18	-0.24	0.33	-0.03
	Commodities			1.00	-0.04	0.04	-0.01	-0.33	0.01	0.10	-0.02	0.37	-0.05	0.00	0.01	-0.04	0.01
	Currencies				1.00	0.13	-0.18	-0.02	-0.23	0.05	0.07	-0.01	0.26	0.30	0.41	0.12	0.37
Value	Equities					1.00	0.05	0.03	0.01	-0.43	-0.08	-0.11	-0.13	0.14	0.21	-0.02	0.26
	Fixed Income						1.00	0.01	0.01	-0.22	-0.35	-0.03	-0.02	-0.01	-0.06	-0.30	0.05
	Commodities							1.00	0.08	-0.16	-0.07	-0.46	0.02	-0.03	-0.06	-0.04	-0.22
	Currencies								1.00	-0.12	-0.22	-0.08	-0.49	-0.06	-0.13	-0.04	-0.14
Momentum	Equities									1.00	0.23	0.20	0.21	-0.15	-0.17	0.12	-0.11
	Fixed Income										1.00	0.11	0.16	0.04	0.00	0.26	0.03
	Commodities											1.00	0.07	0.00	0.02	-0.03	0.06
	Currencies												1.00	-0.10	-0.01	-0.02	0.03
Short Vola	PUT													1.00	0.66	0.02	0.30
Beta	Equities														1.00	0.09	0.35
	Fixed Income															1.00	-0.09
	Commodities																1.00

13. Appendix VI: SAA Weights

Table 23: Weights Inverse Volatility Allocation

The table shows the yearly weights of the inverse volatility allocation across asset classes and strategies from 1995 until 2015. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

Years	Carry				Value				Momentum				Short Vola	Beta		
	EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	EQ	FI	Com
1995	3.2%	9.7%	3.9%	6.0%	5.6%	7.6%	3.3%	7.0%	4.4%	8.9%	3.0%	5.7%	8.6%	2.6%	14.7%	5.8%
1996	3.4%	9.8%	4.0%	6.4%	5.6%	7.8%	3.5%	6.1%	4.4%	8.3%	3.1%	5.6%	9.2%	2.7%	14.4%	5.8%
1997	3.5%	9.9%	4.0%	6.6%	5.4%	8.0%	3.2%	6.3%	4.5%	8.4%	3.0%	5.6%	9.2%	2.8%	14.0%	5.6%
1998	3.4%	10.3%	3.6%	6.5%	5.5%	8.2%	3.2%	6.4%	4.5%	8.7%	2.9%	5.6%	8.7%	2.8%	14.2%	5.6%
1999	3.5%	10.6%	3.7%	6.8%	5.3%	8.8%	3.2%	6.5%	4.1%	9.3%	2.9%	5.6%	6.8%	2.9%	15.0%	5.0%
2000	3.6%	10.7%	3.5%	7.0%	5.3%	9.1%	3.1%	6.7%	4.2%	9.5%	2.6%	5.6%	6.8%	2.9%	14.9%	4.7%
2001	3.6%	11.0%	3.1%	6.3%	5.3%	9.5%	2.7%	6.5%	4.2%	9.8%	2.5%	5.6%	6.8%	3.0%	15.4%	4.6%
2002	3.7%	11.2%	3.0%	6.3%	5.4%	9.9%	2.7%	6.5%	4.3%	10.2%	2.5%	5.6%	5.7%	2.9%	15.6%	4.5%
2003	3.8%	11.0%	3.0%	6.1%	5.5%	10.2%	2.6%	6.6%	4.1%	10.5%	2.5%	5.7%	5.3%	2.9%	15.7%	4.5%
2004	3.9%	10.8%	2.7%	5.9%	5.7%	10.5%	2.5%	6.7%	4.0%	10.7%	2.5%	5.9%	5.3%	2.9%	15.6%	4.4%
2005	4.0%	10.8%	2.7%	5.8%	5.7%	10.6%	2.4%	6.6%	4.1%	10.8%	2.4%	5.9%	5.4%	2.9%	15.5%	4.4%
2006	4.0%	10.8%	2.7%	5.8%	5.8%	10.7%	2.3%	6.6%	4.1%	10.8%	2.4%	5.9%	5.5%	2.9%	15.5%	4.2%
2007	4.1%	10.9%	2.7%	5.7%	5.8%	10.8%	2.3%	6.5%	4.1%	10.9%	2.4%	5.9%	5.5%	3.0%	15.3%	4.1%
2008	4.1%	11.0%	2.7%	5.7%	5.8%	10.9%	2.3%	6.2%	4.2%	11.0%	2.4%	5.8%	5.5%	3.0%	15.3%	4.1%
2009	4.3%	11.3%	2.7%	5.6%	5.8%	11.3%	2.3%	6.0%	4.4%	11.3%	2.4%	5.8%	4.9%	2.8%	15.4%	3.6%
2010	4.4%	11.3%	2.7%	5.4%	5.8%	11.4%	2.3%	6.1%	4.3%	11.5%	2.5%	5.6%	4.8%	2.8%	15.6%	3.6%
2011	4.4%	11.2%	2.7%	5.1%	5.8%	11.6%	2.4%	6.1%	4.4%	11.6%	2.4%	5.6%	4.7%	2.7%	15.7%	3.5%
2012	4.5%	11.3%	2.7%	4.9%	5.7%	11.8%	2.4%	6.1%	4.4%	11.7%	2.5%	5.6%	4.6%	2.7%	15.8%	3.4%
2013	4.5%	11.3%	2.7%	4.9%	5.5%	11.8%	2.4%	6.1%	4.4%	11.8%	2.5%	5.6%	4.6%	2.7%	15.9%	3.4%
2014	4.5%	11.3%	2.7%	4.8%	5.5%	11.9%	2.4%	6.1%	4.4%	11.9%	2.5%	5.6%	4.6%	2.7%	15.7%	3.4%
2015	4.5%	11.4%	2.7%	4.7%	5.5%	12.0%	2.4%	6.1%	4.4%	12.0%	2.5%	5.6%	4.6%	2.7%	15.7%	3.4%
Average	3.9%	10.8%	3.1%	5.8%	5.6%	10.2%	2.6%	6.4%	4.3%	10.5%	2.6%	5.7%	6.1%	2.8%	15.3%	4.3%

Table 24: Weights Global Minimum Variance Allocation

The table shows the yearly weights of the global minimum variance allocation across asset classes and strategies from 1995 until 2015 (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

Years	Carry				Value				Momentum				Short Vola	Beta		
	EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	EQ	FI	Com
1995	0.4%	5.5%	1.0%	5.1%	6.0%	19.4%	2.2%	6.9%	0.0%	9.6%	0.0%	4.0%	6.3%	0.1%	27.2%	6.2%
1996	0.1%	6.3%	0.7%	5.7%	6.3%	18.7%	2.0%	9.5%	0.5%	10.6%	0.8%	4.8%	7.9%	0.1%	21.8%	4.1%
1997	0.5%	7.4%	2.7%	6.1%	6.5%	19.5%	3.6%	7.3%	2.6%	8.1%	0.0%	3.2%	3.9%	0.4%	23.8%	4.3%
1998	0.7%	10.5%	2.2%	5.1%	6.8%	19.1%	2.6%	9.0%	3.3%	8.8%	0.0%	4.1%	2.6%	0.7%	20.9%	3.7%
1999	0.5%	11.7%	2.3%	5.3%	6.5%	19.9%	1.8%	10.4%	4.4%	8.4%	0.6%	5.0%	0.0%	1.1%	21.4%	0.7%
2000	0.4%	12.3%	2.0%	6.1%	6.6%	20.0%	1.9%	10.9%	4.7%	7.9%	0.9%	4.9%	0.0%	1.2%	19.9%	0.0%
2001	0.7%	12.4%	1.8%	6.7%	5.8%	19.6%	1.7%	11.1%	4.1%	7.6%	0.9%	5.2%	0.4%	0.9%	21.0%	0.1%
2002	0.9%	12.3%	1.9%	5.9%	5.4%	20.2%	1.5%	10.6%	3.6%	8.5%	1.0%	5.5%	0.1%	1.1%	21.4%	0.1%
2003	1.2%	11.8%	1.7%	4.1%	4.8%	21.6%	1.7%	9.4%	2.9%	9.7%	1.0%	5.0%	1.1%	1.3%	22.3%	0.2%
2004	1.3%	9.9%	1.2%	2.7%	5.2%	23.1%	2.2%	8.9%	3.2%	11.0%	1.3%	5.2%	2.3%	1.0%	21.5%	0.2%
2005	1.3%	9.4%	1.4%	2.4%	4.9%	23.8%	1.9%	9.5%	3.1%	11.6%	1.0%	5.3%	2.3%	0.8%	21.0%	0.2%
2006	1.3%	9.2%	1.5%	2.3%	4.9%	23.7%	2.0%	9.4%	3.1%	12.1%	0.9%	5.5%	2.4%	0.9%	20.5%	0.3%
2007	1.2%	10.2%	1.2%	1.4%	5.0%	24.1%	1.7%	9.0%	3.1%	12.1%	1.1%	5.4%	2.5%	1.2%	20.4%	0.4%
2008	1.4%	10.2%	1.2%	1.3%	5.3%	24.1%	1.6%	8.4%	3.2%	11.7%	1.1%	5.7%	2.5%	1.4%	20.4%	0.6%
2009	1.1%	10.2%	1.2%	1.7%	5.0%	25.2%	1.4%	9.7%	3.2%	11.9%	0.9%	5.7%	2.7%	0.9%	19.1%	0.1%
2010	1.0%	9.2%	1.1%	1.5%	5.0%	25.4%	1.4%	9.5%	3.2%	12.0%	0.9%	6.1%	2.3%	0.8%	20.1%	0.4%
2011	1.1%	9.4%	1.3%	1.4%	4.7%	25.5%	1.5%	9.6%	3.2%	12.0%	0.7%	5.8%	1.9%	0.8%	20.6%	0.6%
2012	1.1%	9.8%	1.2%	1.2%	4.3%	25.5%	1.5%	9.5%	3.0%	12.1%	0.7%	5.6%	1.5%	0.8%	21.5%	0.7%
2013	1.2%	9.9%	1.2%	1.0%	4.2%	25.4%	1.4%	9.5%	3.0%	12.3%	0.7%	5.7%	1.6%	0.7%	21.5%	0.7%
2014	1.2%	10.2%	1.2%	0.9%	4.0%	25.7%	1.4%	9.5%	3.1%	12.6%	0.7%	5.6%	1.7%	0.7%	21.0%	0.6%
2015	1.2%	9.9%	0.9%	0.7%	3.9%	25.7%	1.4%	9.3%	3.1%	13.1%	0.7%	5.6%	1.9%	0.6%	21.5%	0.6%
Average	0.9%	9.9%	1.5%	3.3%	5.3%	22.6%	1.8%	9.4%	3.0%	10.6%	0.8%	5.2%	2.3%	0.8%	21.4%	1.2%

Table 25: Weights Maximum Sharpe Ratio Allocation

The table shows the yearly weights of the maximum Sharpe ratio allocation across asset classes and strategies from 1995 until 2015. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

Years	Carry				Value				Momentum				Short Vola	Beta		
	EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	EQ	FI	Com
1995	3.4%	4.3%	0.0%	11.1%	13.4%	16.3%	4.8%	5.7%	0.3%	0.0%	6.6%	0.0%	30.7%	0.8%	0.4%	2.3%
1996	3.3%	6.9%	0.0%	6.2%	9.6%	16.9%	4.9%	3.8%	2.8%	0.0%	5.1%	0.6%	22.6%	0.9%	13.3%	3.1%
1997	3.0%	10.0%	0.0%	6.4%	10.0%	16.0%	6.1%	4.0%	3.3%	0.0%	3.7%	0.0%	21.5%	0.9%	11.4%	3.7%
1998	2.8%	11.8%	0.0%	8.4%	9.2%	16.2%	4.7%	6.0%	4.2%	0.0%	3.3%	0.1%	24.4%	0.0%	5.2%	3.7%
1999	3.4%	8.1%	0.6%	9.1%	7.3%	16.9%	3.5%	8.8%	7.3%	0.0%	3.5%	4.0%	9.2%	0.2%	17.9%	0.0%
2000	3.6%	10.1%	1.5%	9.7%	8.0%	17.6%	3.3%	9.2%	7.8%	0.0%	3.2%	3.7%	9.1%	1.2%	12.2%	0.0%
2001	3.5%	9.7%	1.4%	10.3%	7.2%	16.6%	2.5%	9.9%	6.2%	0.0%	3.6%	3.2%	9.8%	0.2%	15.8%	0.0%
2002	3.5%	10.8%	2.3%	8.4%	7.6%	16.5%	3.0%	8.4%	6.0%	0.0%	3.5%	4.2%	5.2%	0.3%	20.4%	0.0%
2003	3.9%	9.2%	2.0%	9.1%	7.4%	17.1%	2.8%	8.9%	5.4%	0.0%	3.0%	4.4%	4.5%	0.4%	22.0%	0.0%
2004	4.3%	7.1%	1.4%	9.2%	8.8%	17.9%	3.2%	8.3%	5.9%	0.0%	3.3%	4.5%	6.3%	0.3%	19.6%	0.0%
2005	4.2%	7.3%	2.0%	8.8%	9.3%	17.9%	3.1%	8.4%	6.1%	0.0%	3.0%	4.3%	6.7%	0.4%	18.6%	0.0%
2006	4.5%	6.8%	2.4%	8.4%	9.7%	17.4%	3.1%	8.3%	6.5%	0.0%	2.6%	5.1%	6.6%	0.8%	17.7%	0.0%
2007	4.8%	9.0%	2.2%	6.4%	10.1%	17.8%	2.7%	7.0%	6.2%	0.0%	3.3%	4.7%	7.4%	1.6%	16.9%	0.0%
2008	5.1%	10.4%	1.8%	5.6%	9.7%	18.8%	2.6%	6.3%	6.4%	0.0%	3.5%	4.5%	7.0%	2.1%	16.3%	0.0%
2009	4.8%	11.5%	2.4%	4.9%	6.6%	19.4%	2.7%	10.5%	6.0%	0.0%	2.9%	5.8%	4.9%	0.9%	16.7%	0.0%
2010	4.6%	10.4%	2.4%	5.0%	6.2%	20.6%	2.4%	10.4%	5.6%	0.0%	2.7%	6.0%	5.1%	0.6%	17.9%	0.0%
2011	4.5%	12.0%	2.8%	4.4%	5.3%	20.0%	2.3%	10.3%	5.4%	0.0%	2.2%	5.8%	5.0%	0.6%	19.4%	0.0%
2012	5.0%	13.2%	2.9%	4.3%	4.0%	19.4%	2.4%	9.9%	4.6%	0.0%	2.4%	5.0%	4.9%	0.1%	22.0%	0.0%
2013	4.7%	13.3%	2.9%	4.0%	3.8%	18.9%	2.4%	10.0%	4.4%	0.0%	2.2%	5.3%	4.8%	0.2%	23.0%	0.0%
2014	5.0%	13.9%	2.9%	3.0%	3.5%	18.9%	2.5%	10.3%	4.5%	0.0%	2.4%	5.7%	5.1%	0.5%	21.8%	0.0%
2015	5.6%	13.2%	2.2%	2.2%	2.8%	18.2%	2.6%	9.3%	4.4%	0.0%	2.7%	5.7%	5.7%	0.3%	25.0%	0.0%
Average	4.2%	9.9%	1.7%	6.9%	7.6%	17.9%	3.2%	8.3%	5.2%	0.0%	3.3%	3.9%	9.8%	0.6%	16.8%	0.6%

Table 26: Weights Risk Parity Allocation

The table shows the yearly weights of the risk parity allocation across asset classes and strategies from 1995 until 2015. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

Years	Carry				Value				Momentum				Short Vola	Beta		
	EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	EQ	FI	Com
1995	2.5%	7.6%	3.2%	4.7%	7.5%	17.0%	3.8%	6.7%	3.9%	7.7%	2.4%	4.9%	7.7%	3.2%	11.3%	5.9%
1996	2.6%	7.7%	3.3%	4.8%	7.2%	16.5%	3.7%	7.5%	4.0%	7.6%	2.6%	5.1%	7.8%	2.9%	11.4%	5.3%
1997	2.8%	7.9%	4.1%	5.2%	7.6%	16.9%	4.5%	6.8%	4.6%	7.0%	2.1%	4.3%	6.5%	2.9%	11.8%	5.1%
1998	2.9%	9.1%	3.6%	5.2%	7.6%	16.2%	3.8%	7.9%	5.0%	7.5%	2.0%	5.0%	6.2%	2.7%	10.4%	5.2%
1999	2.9%	9.1%	3.8%	5.7%	7.1%	16.5%	3.3%	8.0%	5.8%	7.2%	2.2%	6.1%	3.7%	2.6%	12.2%	3.8%
2000	2.9%	9.8%	3.5%	5.9%	7.1%	16.4%	3.4%	8.5%	5.9%	6.9%	2.4%	5.8%	3.8%	2.5%	12.0%	3.2%
2001	2.9%	10.2%	3.1%	5.9%	6.9%	15.9%	3.6%	8.9%	5.5%	7.2%	2.3%	5.9%	3.7%	2.4%	12.5%	3.1%
2002	2.9%	10.4%	3.1%	5.3%	6.9%	16.1%	3.5%	8.3%	5.4%	7.5%	2.3%	6.3%	3.2%	2.4%	13.5%	2.9%
2003	3.2%	10.1%	3.0%	4.7%	6.8%	16.6%	3.6%	7.7%	5.1%	7.9%	2.4%	6.0%	3.5%	2.6%	13.8%	3.1%
2004	3.3%	9.3%	2.7%	4.1%	6.9%	17.4%	4.2%	7.5%	5.1%	8.3%	2.5%	6.1%	3.9%	2.6%	13.0%	3.0%
2005	3.4%	9.1%	2.8%	4.0%	6.7%	17.8%	4.0%	8.2%	5.1%	8.5%	2.4%	6.1%	3.9%	2.6%	12.5%	3.0%
2006	3.5%	9.1%	2.8%	4.0%	6.6%	17.7%	4.0%	8.2%	5.0%	8.6%	2.4%	6.2%	4.0%	2.6%	12.4%	3.0%
2007	3.5%	9.4%	2.7%	3.7%	6.6%	17.8%	3.7%	8.1%	4.9%	8.7%	2.6%	6.1%	4.1%	2.7%	12.3%	3.1%
2008	3.5%	9.4%	2.6%	3.7%	6.6%	18.0%	3.6%	8.1%	4.9%	8.8%	2.5%	6.0%	4.0%	2.7%	12.3%	3.1%
2009	3.4%	9.2%	2.5%	3.6%	5.8%	19.2%	3.6%	10.3%	5.0%	8.6%	2.3%	6.2%	3.5%	2.3%	11.8%	2.5%
2010	3.3%	9.0%	2.5%	3.4%	5.8%	19.4%	3.6%	10.3%	5.1%	8.7%	2.4%	6.8%	3.4%	2.1%	11.9%	2.5%
2011	3.3%	9.5%	2.6%	3.1%	5.5%	19.3%	3.6%	10.5%	5.1%	8.7%	2.3%	6.5%	3.1%	2.0%	12.4%	2.5%
2012	3.4%	10.2%	2.6%	2.9%	5.3%	19.0%	3.7%	10.6%	4.9%	8.8%	2.3%	6.2%	2.9%	1.9%	13.0%	2.5%
2013	3.4%	10.3%	2.5%	2.8%	5.2%	18.8%	3.7%	10.6%	4.9%	9.0%	2.3%	6.3%	2.9%	1.8%	13.0%	2.4%
2014	3.4%	10.5%	2.5%	2.8%	5.0%	19.0%	3.7%	10.5%	5.0%	9.2%	2.3%	6.1%	3.0%	1.8%	12.7%	2.4%
2015	3.5%	10.4%	2.4%	2.7%	4.9%	18.8%	3.7%	10.3%	5.1%	9.4%	2.4%	6.2%	3.0%	1.8%	13.1%	2.3%
Average	3.2%	9.4%	3.0%	4.2%	6.5%	17.6%	3.7%	8.7%	5.0%	8.2%	2.3%	5.9%	4.2%	2.4%	12.3%	3.3%

Table 27: Weights Most Diversified Portfolio Allocation

The table shows the yearly weights of the most diversified portfolio allocation across asset classes and strategies from 1995 until 2015. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

Years	Carry				Value				Momentum				Short Vola	Beta		
	EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	FI	Com	FX	EQ	EQ	FI	Com
1995	1.4%	8.4%	2.7%	3.2%	10.1%	20.3%	4.0%	5.0%	5.2%	9.9%	2.4%	3.6%	8.7%	4.5%	5.0%	5.7%
1996	1.4%	7.8%	2.3%	4.2%	8.6%	18.7%	3.4%	9.1%	4.4%	9.6%	2.3%	4.9%	7.2%	3.4%	8.3%	4.2%
1997	1.9%	8.1%	4.3%	4.5%	9.4%	19.4%	5.0%	6.9%	6.4%	7.9%	1.0%	3.4%	1.7%	3.8%	12.0%	4.4%
1998	1.8%	9.6%	3.9%	4.8%	9.7%	18.9%	4.0%	9.1%	7.1%	8.6%	0.7%	5.0%	1.8%	3.6%	7.3%	4.1%
1999	1.7%	9.5%	3.8%	5.4%	9.8%	18.8%	3.5%	9.5%	8.0%	6.5%	1.2%	6.4%	0.0%	3.1%	10.5%	2.3%
2000	1.6%	10.8%	3.3%	6.0%	9.9%	18.6%	3.8%	10.0%	8.1%	5.6%	1.8%	5.9%	0.0%	3.1%	10.3%	1.1%
2001	1.7%	10.4%	3.4%	6.9%	8.9%	17.6%	4.0%	10.8%	7.2%	5.8%	1.9%	6.3%	0.0%	2.6%	11.1%	1.3%
2002	2.0%	10.8%	3.2%	5.9%	8.4%	17.9%	3.6%	10.3%	6.6%	6.1%	2.0%	6.8%	0.1%	2.8%	12.1%	1.3%
2003	2.4%	10.6%	3.0%	4.3%	8.3%	18.7%	4.0%	8.9%	6.4%	6.2%	2.3%	6.5%	1.4%	3.2%	12.2%	1.6%
2004	2.6%	9.7%	2.7%	2.9%	8.5%	19.6%	4.9%	8.2%	6.7%	6.9%	2.6%	6.7%	2.4%	3.2%	10.9%	1.6%
2005	2.7%	9.1%	2.9%	2.7%	8.0%	20.1%	4.6%	9.4%	6.4%	7.6%	2.5%	6.9%	2.4%	3.0%	10.1%	1.7%
2006	2.8%	9.0%	2.9%	2.5%	7.8%	19.8%	4.6%	9.4%	6.2%	7.9%	2.5%	7.0%	2.4%	3.0%	10.2%	1.8%
2007	2.8%	9.7%	2.7%	1.5%	7.7%	19.8%	4.5%	9.2%	6.1%	7.6%	2.9%	7.0%	2.5%	3.2%	10.5%	2.3%
2008	2.8%	9.5%	2.5%	1.6%	7.8%	19.9%	4.3%	9.5%	6.1%	7.7%	2.8%	7.3%	2.2%	3.4%	10.4%	2.2%
2009	2.4%	9.5%	2.5%	1.7%	7.2%	21.1%	4.0%	11.9%	6.1%	7.9%	2.4%	7.5%	2.6%	2.6%	8.9%	1.6%
2010	2.3%	9.0%	2.3%	1.5%	7.1%	21.2%	3.9%	12.0%	6.1%	7.6%	2.5%	8.2%	2.5%	2.4%	9.4%	1.9%
2011	2.3%	10.0%	2.5%	1.1%	6.5%	20.9%	4.0%	12.1%	6.0%	7.2%	2.3%	7.8%	2.0%	2.4%	10.5%	2.2%
2012	2.5%	10.8%	2.5%	0.8%	5.9%	20.4%	4.1%	12.2%	5.5%	7.1%	2.3%	7.6%	1.6%	2.3%	12.1%	2.4%
2013	2.5%	11.0%	2.4%	0.5%	6.0%	20.2%	4.1%	12.1%	5.7%	7.3%	2.3%	7.8%	1.7%	2.2%	12.0%	2.3%
2014	2.5%	11.4%	2.4%	0.6%	5.8%	20.6%	4.0%	12.0%	5.9%	7.6%	2.3%	7.4%	1.8%	2.1%	11.5%	2.2%
2015	2.6%	11.0%	2.1%	0.3%	5.6%	20.3%	4.1%	11.7%	6.0%	7.8%	2.4%	7.5%	2.1%	2.1%	12.2%	2.1%
Average	2.2%	9.8%	2.9%	3.0%	7.9%	19.7%	4.1%	10.0%	6.3%	7.5%	2.2%	6.5%	2.2%	3.0%	10.4%	2.4%

Table 28: Weights Relative Carry Allocation

The table shows the yearly weights of the relative carry allocation across asset classes and strategies from 1995 until 2015. (source: Own calculations with data from Bloomberg, Asness, Moskowitz and Pedersen (2013), AQR and Kenneth French's website).

Years	Equities				Fixed Income				Commodities				Short Vola	Currencies		
	Carry	Value	Mom	Beta	Carry	Value	Mom	Beta	Carry	Value	Mom	Beta	EQ	Carry	Value	Mom
1995	4.5%	7.5%	5.9%	3.9%	7.2%	5.0%	6.9%	9.6%	4.3%	3.6%	2.7%	5.7%	11.6%	6.2%	8.5%	6.7%
1996	4.4%	6.3%	5.6%	3.7%	6.7%	4.9%	6.6%	8.5%	5.5%	4.5%	3.4%	7.2%	12.7%	6.4%	7.0%	6.7%
1997	3.6%	5.1%	4.6%	3.2%	6.5%	5.0%	6.5%	8.0%	6.3%	4.9%	4.0%	7.9%	12.6%	7.0%	7.5%	6.9%
1998	3.7%	5.1%	4.6%	3.3%	6.8%	5.3%	6.9%	8.6%	4.5%	3.7%	3.0%	6.1%	12.9%	8.3%	9.1%	8.2%
1999	3.5%	4.6%	3.9%	3.2%	8.0%	6.7%	8.6%	10.8%	3.1%	2.5%	2.1%	3.5%	10.8%	9.7%	10.0%	8.9%
2000	5.0%	6.4%	5.5%	4.4%	7.6%	6.3%	7.9%	9.7%	2.8%	2.4%	1.9%	3.4%	10.6%	9.0%	9.0%	8.0%
2001	5.2%	6.6%	5.6%	4.7%	7.6%	6.2%	7.6%	9.6%	2.9%	2.2%	2.1%	3.7%	10.7%	8.6%	8.7%	8.1%
2002	4.6%	5.9%	4.9%	3.9%	7.7%	6.5%	7.8%	9.7%	4.3%	3.5%	3.3%	5.6%	8.2%	8.4%	8.2%	7.6%
2003	4.4%	5.7%	4.6%	3.6%	8.0%	6.9%	8.3%	10.2%	4.4%	3.5%	3.3%	5.6%	7.3%	7.8%	8.5%	7.7%
2004	4.8%	6.1%	4.7%	3.7%	9.1%	8.0%	9.7%	11.6%	4.1%	3.5%	3.3%	5.7%	8.2%	5.4%	6.4%	5.8%
2005	5.7%	7.2%	5.6%	4.3%	8.4%	7.5%	8.9%	10.6%	4.3%	3.6%	3.5%	6.0%	7.9%	5.0%	6.0%	5.5%
2006	5.8%	7.4%	5.7%	4.4%	8.1%	7.2%	8.5%	10.1%	4.7%	4.0%	3.9%	6.4%	7.7%	4.9%	5.9%	5.3%
2007	5.7%	7.3%	5.6%	4.2%	8.1%	7.3%	8.6%	9.9%	4.6%	3.8%	3.7%	6.1%	8.2%	5.1%	6.3%	5.7%
2008	5.6%	7.0%	5.4%	4.0%	8.4%	7.6%	8.9%	10.2%	3.9%	3.3%	3.3%	5.3%	8.3%	5.7%	6.8%	6.4%
2009	6.0%	7.0%	5.9%	3.7%	8.5%	7.9%	9.0%	10.2%	3.5%	3.0%	3.1%	4.0%	6.7%	6.3%	7.5%	7.7%
2010	3.7%	4.3%	3.6%	2.1%	9.3%	8.9%	9.9%	11.3%	4.1%	3.5%	3.5%	4.6%	7.0%	7.1%	8.6%	8.3%
2011	3.8%	4.5%	3.7%	2.2%	9.8%	9.2%	10.3%	11.7%	4.3%	3.6%	3.6%	4.8%	7.0%	6.5%	7.6%	7.4%
2012	3.8%	4.2%	3.6%	2.1%	9.3%	8.9%	9.9%	11.2%	3.9%	3.3%	3.3%	4.4%	11.3%	6.3%	7.3%	7.1%
2013	3.7%	4.0%	3.5%	2.0%	9.1%	8.7%	9.7%	11.0%	4.3%	3.7%	3.7%	4.7%	13.2%	5.7%	6.6%	6.4%
2014	4.1%	4.5%	3.9%	2.3%	9.4%	9.1%	10.0%	11.2%	4.3%	3.7%	3.7%	4.7%	10.5%	5.6%	6.6%	6.5%
2015	3.8%	4.1%	3.6%	2.1%	8.9%	8.5%	9.5%	10.5%	3.2%	2.9%	2.9%	3.6%	12.9%	7.0%	8.3%	8.2%
Average	4.6%	5.8%	4.8%	3.4%	8.2%	7.2%	8.6%	10.2%	4.2%	3.5%	3.2%	5.2%	9.8%	6.8%	7.6%	7.1%