MASTER'S THESIS

Alternative Risk Premia Investing

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HEC MONTRÉAL

Declaration of Authorship

I, Julien HEBERT NGUYEN, declare that this thesis titled, "Alternative Risk Premia Investing" and the work presented in it are my own. I confirm that:

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- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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"Immature poets imitate; mature poets steal; bad poets deface what they take, and good poets make it into something better, or at least something different. The good poet welds his theft into a whole of feeling which is unique, utterly different from that from which it was torn; the bad poet throws it into something which has no cohesion. A good poet will usually borrow from authors remote in time, or alien in language, or diverse in interest."

T.S. Eliot

Abstract

Alternative Risk Premia Investing

by Julien HEBERT NGUYEN

We propose a systematic portfolio construction framework that combines alternative risk premia strategies in a robust investment portfolio. In the frame of this paper, we developed four strategies that capture smart beta, value, carry, and momentum risk premia. In the spirit of reproducible research, we clearly defined the instruments, rules, trading signals, and order sizing methodologies used in each of the strategies. To make our findings relevant to academics and practitioners alike, transaction costs impacts were precisely modelled and assessed. The strategies presented herein were created to account for the trading constraints faced by typical investors. They are implementable by anyone transacting futures contracts. Backtests are coded in the R language. Critical code elements are presented throughout the paper for the reader's benefit. Our results presented strong evidence that transactions costs and rebalancing frequencies have a very significant impact on the return characteristics of different risk premia strategies. We provided an in-depth performance analysis of every strategy in light of these two important factors.

The strategies returns are then used to investigate the performance of different portfolio construction methodologies. We considered only robust frameworks, thus omitting any method requiring the forward estimation of returns. The portfolio properties of the frameworks used are well documented in the case of traditional risk premia. However, their resulting characteristics when applied to alternative risk premia portfolios are undocumented. Our results show that these approaches retain their strengths and weaknesses irrespective of the risk premia.

Our research contributes to the field of Financial Engineering in the following ways. First, it establishes a transparent reproducible framework by which to develop, implement, and analyze alternative risk premia strategies under realistic trading conditions. This is of importance because the current literature on alternative risk premia often bases its conclusions on strategies that were modelled in the absence of transaction costs. This paper demonstrate that such results provide little context as to the characteristics of those premia. We suspect certain published strategies to even be unprofitable over the long run. Secondly, our investigations on the different portfolio construction techniques contributes empirical results to a body of knowledge that is scarce. There currently exists no consensus around which portfolio construction methodologies to favour for alternative risk premia. Finally, this research represents a stepping stone; we hope to directly use our findings to investigate other potential applications of alternative risk premia investing. These applications are discussed in detail in our concluding chapter.

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Thank you!

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List of Abbreviations

ERC	**E**qual **R**isk **C**ontribution
PPP	**P**urchasing **P**ower **P**arity
FX	**F**oreign E**x**change
EMA	**E**xponential **M**oving **A**verage
ERP	**E**quity **R**isk **P**remium
IRP	**I**nterest **R**ate **P**arity
GARCH	**G**eneralized **A**uto**R**egressive **C**onditional **H**eteroskedasticity
MV	**M**inimum **V**ariance

For my father, because hard work, passion, and integrity are rewarded after all. . .

Chapter 1

Investment Context

1.1 The Rise of Alternative Risk Premia Investing

"Diversification is the only free lunch". This old adage has long been repeated and heeded by institutional and retail investors alike. The mathematics of portfolio construction clearly demonstrate the value associated to identifying different uncorrelated (or lowly) correlated risk premia and incorporating them in a portfolio. This search was made even more important with the advent of the mean-variance framework; the latter providing portfolio managers with a tool to quantify the benefits of adding new assets to a portfolio. Having mastered traditional risk premia investing, investors are now increasingly seeking new sources of premia.

This search has been going on long before the discovery of the CAPM. Throughout the years, academic researchers have identified multiple sources of returns that can be accessed systematically. The firsts were additional factors explaining the equity risk premium. Fama and French are, to this day, renowned for pioneering this field. However, since the 90's, it is through hedge funds that many new uncorrelated return factors were identified. Practitioners and academics jumped on the bandwagon identifying an ever expanding set of these systematic sources of returns in all asset classes. As CTA's, Global macro hedge funds, and multi-strategy hedge funds contributed to the popularization of those strategies they became increasingly accepted by the research community. Academics categorized these new factors under one term: alternative risk premia.

The term alternative risk premia sometimes lends itself to misinterpretation as it encompasses more than strictly risk premium. We feel the best definition of what an alternative risk premia is, comes from a 2016 paper written by Lyxor asset management [1]. It quotes: "In practice, alternative risk premia are systematic risk factors that can help to explain the past returns of diversified portfolios. They may be risk premia in a strict sense, but also market anomalies or common strategies.". Any systematic strategy that resulted in consistent positive returns over many economic cycles, and whose returns are unexplained by traditional risk premia (i.e. long-only exposure to equity / bonds) can therefore be described as an alternative risk premia.

At the time of this writing, the alternative risk premia funds have grown into an industry of their own. The post financial crisis regulatory framework contributed to this. By limiting investment banks proprietary trading activities through Dodd-Frank, the banks were forced to restructure their activities. Rather than closing these lucrative desks, they opted to offer the strategies to outside investors. This gave rise to a whole industry around systematic strategies swap. Hedge funds and traditional asset managers have now also embraced alternative risk premia investing. They are increasingly seen separating their traditional "alpha" offering[1] from their alternative risk premia funds. The fees on those funds are typically in-between those of a typical "alpha" and "beta" portfolios. These efforts have not been in vain; today's investments in alternative risk premia are quickly gaining market adoption. The following figure presents the results of 2016 survey by Russell [2] in which they conclude that: "This year's survey provided evidence of the rapidly growing interest in this area, and a couple of things stood out in the results."

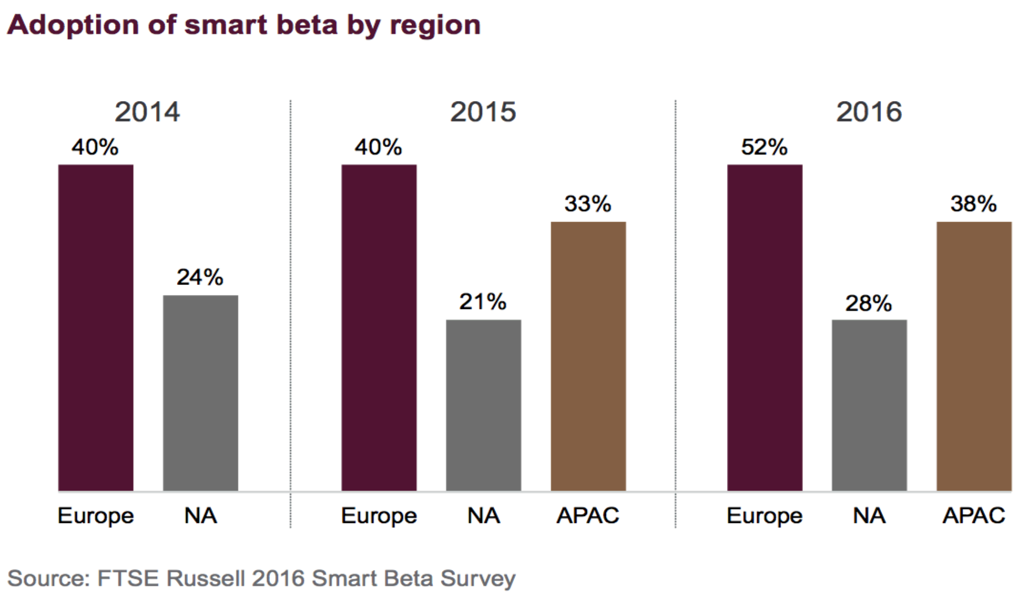

FIGURE 1.1: The rise of factor investing

The fact that alternative risk premia cover all assets classes, as well as the large scope of their definition, makes it difficult to define or isolate "pure" alternative risk premia returns. Indeed, a particular risk premium can be accessed in many different ways. Each are dependent on the strategies parameters and implementation. Because of this, researchers can adopt two different stances toward risk premia research. The first consists in aggregating commercially available risk premia indices together by filtering for similarities across them. This demands access to these indices which is not always trivial as they are oftentimes private data of investment banks and asset managers. Even with access to the data, this approach is, in our opinion, not realistic. It requires one to perform a thorough analysis of all these indices by diligently reading each of their rule-books and prospectuses. This is a Herculean task at best. Consider for instance that Harvey and al. have identified more than 200 risk factors and market anomalies for the equity asset class alone [3]. Furthermore, as illustrated in the below figure [1], this number keeps on growing year after year. Should one consider all asset classes, the number of risk premia quickly reaches the thousand's.

[1] Which typically command high fees (2% & 20%)

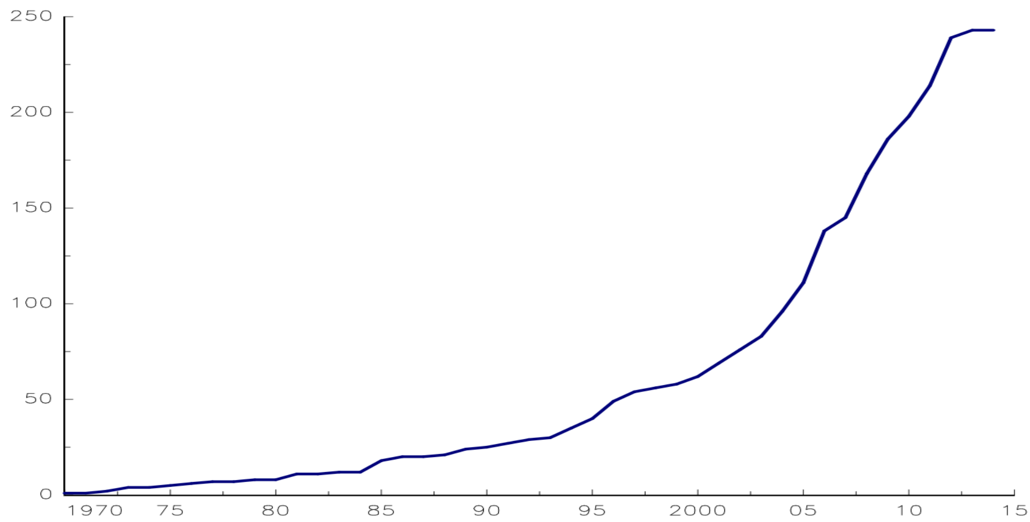

FIGURE 1.2: Equity Risk Premia Published In Time

The other approach consists in formulating one's own strategies and backtest them. This is the approach favoured in this paper. Its structure differs from that of traditional academic papers and, is as follows: In chapter 2, we present the datasets and backtest specifications adopted to develop the strategies presented herein. Chapters 3 to 6 each focus on a strategy that belongs to four alternative risk premia (risk parity, value, carry, and momentum). In each chapter, we cover its strategy's theoretical foundations by thoroughly reviewing the current academic literature pertaining to it and then, proceed to describe its investment universe, its signal construction and its final implementation. The strategies are implemented exclusively through futures instruments, and backtested under "realistic" trading cost assumption. Proper care is applied to quantify the impact of trading costs and rebalancing frequency on each strategy. Our goal is to build them so that they are accessible to both, retail and institutional investors, who have access to leverage and derivatives. This means that we do not want the strategies to require excessive or continuous trading. These concerns are discussed in the final section of these chapters as part of the strategy's performance analysis. In chapter 7, we investigate different portfolio construction approaches through which we aggregate the strategies in a portfolio. Again, we conduct a literature review of the different portfolio construction methodologies used today. Our literature review, as well as the content of this section, focus on testing robust portfolio construction methodologies. We present the reader with our findings so that he may use them in integrating these risk premia together. Chapter 8 concludes our research by outlining future investigations that will be based on this paper's results.

Chapter 2

Data & Backtest Specifications

In the spirit of reproducible research, extra care was taken in developing and modelling the strategies contained herein. We are confident that our results represent those of strategies that are investable. An investor with access to leverage and bearing similar trading costs to those used in our backtests should be able to efficiently replicate our returns. The specificities of our modelling methodology are discussed below.

2.1 Datasets

2.1.1 Sources

The strategies presented in this paper invest solely in listed (i.e. exchange traded) futures instruments. Unless stated otherwise, the data we used comes directly from Bloomberg. Futures instruments are clearly identified by their Bloomberg Terminal symbols. All other data sets that we used are accompanied by their corresponding Bloomberg Terminal symbols or command.

2.1.2 Continuous Futures Adjustments

Futures instruments expire and need to be rolled on a calendar basis for an investor to maintain its exposure to the underlying asset's returns. When devising trading strategies using futures, one needs to account for the term structure's impact over time. We factored the impact of contango and backwardation in the instruments' prices by using Bloomberg's generic continuous series data. The rollover settings we used are shown below:

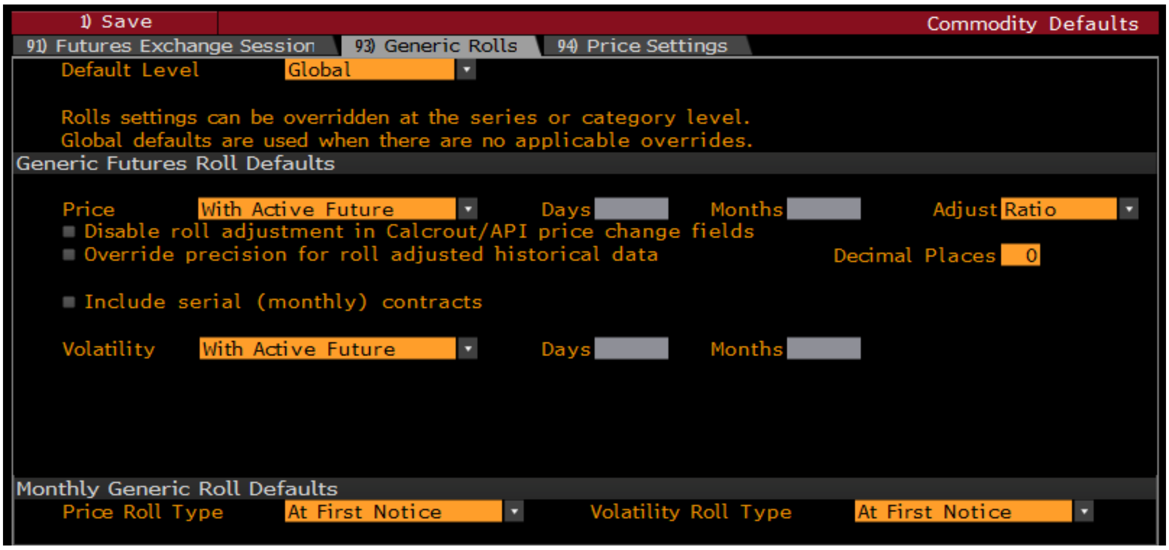

FIGURE 2.1: Bloomberg - Futures Settings

The settings assume that the contracts roll on their first notice date and, that the continuous price series are derived using the proportional adjustment approach. This approach consists in adjusting two consecutive futures prices by multiplying them by the ratio of the older contract's to the newer contract's trading price on the day of the adjustment. There are other forward adjustments methods, and they each present advantages and disadvantages. The back-forward (Panama) and the rollover methods, are two other popular methods by which one can derive continuous futures prices. We favour the proportional adjustment approach because its computation methodology requires very few assumptions. For more information on continuous futures adjustments, we direct the reader to Schwager's treatment of the subject [4], and to the Quanstart's online tutorial [5].

2.1.3 Periods

For each strategy backtested, we worked with the longest data history as possible. As futures instruments differ in trading history, certain strategies have longer backtest periods than others. This being said, we made sure to present at least 10 years of returns data. This ensures that the strategies are analyzed over the span of a full economic cycle[1].

2.2 Backest Parameters

2.2.1 Slippage

We backtested our strategies over different rebalancing frequencies. Upon each rebalancing, a full day of slippage is applied. This creates a realistic time delay between the moment a trade signal is received and its completion. We believe that a full day is ample time, even for large institutional investors who require more liquidity, to complete their orders. As institutional futures traders often execute their trades using market

[1]As defined by NBER's average cycle duration (http://www.nber.org/cycles.html.).

participation algorithms [2], a day of slippage is a realistic assumption with which to work.

2.2.2 Transactions Costs

Transaction costs of 1 basis point are applied to every trade. To clarify, these costs are a function of the portfolio's value being traded. For example, should the whole portfolio turnover, then we'd assume a full basis point of trading impacts on that day's return. These costs should correspond to what the average futures trader is expected to pay in commissions and clearing. However, since transactions costs can have a material impact on a strategy's returns and, given that no two investors are alike, we present strategy backtests using different trading costs.

[2] Passive futures traders generally alternate between implementation shortfall, or TWAP.

Chapter 3

Risk Parity Strategy

3.1 Literature Review

The asset allocation problem is one that has long been studied by academics and financial professionals. Long before the advent of risk parity portfolios, Markowitz, in its seminal paper title Portfolio Selection [6], proposed the mean-variance model as a formal solution to this problem. By positing that investors are risk averse and thus exhibit utility functions that are increasing and concave, one can prove that the optimal portfolio is the one with maximum expected return for a given variance (risk) level. Depending on an investor's risk appetite, one can use this framework to obtain the best portfolio. This asset allocation model has been prevalently used for the last 40 years.

For all its elegance, the mean-variance model comes plagued by technical difficulties that arise when implementing it in practice. Indeed, it relies heavily on its input parameters which are themselves hard to estimate. The expected-return estimations of a portfolio's assets are especially difficult to obtain with precision as described by Merton many years later [7]. Practitioners often use the average long-term excess return of the asset; a measure that fails to account for changes in the market risk level. The model's variance inputs are also non-trivial to estimate, especially for portfolios that contain a large amount of assets. Small perturbations in the covariance matrix can result in large weight shifts for the portfolio exposing its user to detrimental trading costs. Through market crises, asset managers came to realize that the mean-variance model might not be as robust in practice. In the last years, a large body of research focused on developing robust methods around these estimation issues. Ledoit and Wolf [8], Jagannathan and Ma [9], and DeMiguel et al. [10] all provide insights into these improvements.

Even with these improvements, mean-variance portfolios suffered large losses during the last two major financial crises (2000, 2008). This led to a renewed interest in asset allocation frameworks, many of whom were not optimization based. The risk parity portfolios are one of these frameworks. The main objective of risk parity portfolios is to address robustness issues inherent to their mean-variance counterparts. The first paper on the subject was authored by Edward Qian, a portfolio manager at Panagora asset management [11]. In it, the author demonstrates that using an asset's risk contribution to a portfolio makes for an accurate metric of loss contribution. Working with risk contributions instead of variance lead to efficient portfolios in real world terms. Indeed, risk parity portfolios exhibit many desirable properties. They enforce a degree of diversification, as assets are guaranteed to have non-zero weights, and they remain mean-variance optimal under a specific set of assumptions. These assumptions are not discussed herein, but are presented in a paper authored by Maillard, Roncalli, and

Teiletche [12]. One of these authors, Roncalli, also provides a comprehensive treatment of the subject in one of his books [13].

The last 5 years have seen the use of risk parity portfolios increase significantly among institutional managers. Hedge funds and asset managers have contributed to their popularity, but academic researchers have also helped fostering this approach. There remains, nonetheless, many different methodologies by which one can implement these portfolios. Choices around a portfolio's leverage, its rebalancing frequency, and its investment universe are critical in successfully implementing this strategy. We address those below.

3.2 Investment Universe

The table below contains the instruments traded in the strategy. Risk parity portfolios transact assets that exhibit and outright risk premia. Currency futures are therefore absent from the strategy's tradeable assets because they present no long term holding benefits.

Ticker	Bloomberg Code	Description	Asset Class
ES1	ES1 Index	E-mini S&P 500 Future	Equity
NK1	NK1 Index	Nikkei 225 Index Future	Equity
VG1	VG1 Index	Euro STOXX 50 Index Future	Equity
PT1	PT1 Index	S&P Toronto 60 Future	Equity
XP1	XP1 Index	ASX SPI 200 Future	Equity
TY1	TY1 Comdty	US Treasury 10-Year Future	Fixed Income
RX1	RX1 Comdty	German Government Euro Bund Future	Fixed Income
JB1	JB1 Comdty	Japanese Government Bond 10-Year Future	Fixed Income
US1	US1 Comdty	US Treasury Long Bond Future	Fixed Income
CN1	CN1 Comdty	Canadian Governement Bond 10-Year Future	Fixed Income
FV1	FV1 Comdty	US Treasury 5-Year Note Future	Fixed Income
CL1	CL1 Comdty	Crude Oil Future	Commodity
GC1	GC1 Comdty	Gold Future	Commodity
HG1	HG1 Comdty	Copper Future	Commodity
NG1	NG1 Comdty	Natural Gas Future	Commodity
LC1	LC1 Comdty	Live Cattle Future	Commodity
S_1	S 1 Comdty	Soybean Future	Commodity
W_1	W 1 Comdty	Wheat Future	Commodity
C_1	C 1 Comdty	Corn Future	Commodity
SB1	SB1 Comdty	Sugar Future	Commodity
LH1	LH1 Comdty	Lean Hog Future	Commodity
FC1	FC1 Comdty	Feeder Cattle Future	Commodity
QS1	QS1 Comdty	Gas Oil Future	Commodity
CC1	CC1 Comdty	Cocoa Future	Commodity
CO1	CO1 Comdty	Brent Oil Future	Commodity
SI1	SI1 Comdty	Silver Future	Commodity

TABLE 3.1: Risk Parity Strategy - Investment Universe

3.3 Signals & Order Sizing

We specify the risk parity's portfolio problem using a notation similar to that of Thierry Roncalli [12]. For a portfolio of n assets, where $w = (w_1, ..., w_n)$ is the weight vector of each asset in the portfolio, if we consider $\mathcal{R}(w_1, ..., w_n)$ to be a coherent and convex risk measure, we can express each asset's contribution to the portfolio's risk as:

$$\begin{aligned}\mathcal{R}(w_1, ..., w_n) &= \sum_{i=1}^{n} w_i \frac{\partial \mathcal{R}(w_1, ..., w_n)}{\partial w_i} \\ &= \sum_{i=1}^{n} \phi_i(w_1, ..., w_n)\end{aligned}$$

where

ϕ_i corresponds to the contribution asset i to the total portfolio risk

Replacing the general risk measure (ϕ) by a specific risk measure σ that corresponds to the portfolio's variance. We can express the portfolio's risk as:

$$\begin{aligned}\sigma(w) &= \sqrt{w^T \Sigma w} \\ &= \sum_{i=1} w_i^2 \sigma_i^2 + \sum_{i=1} \sum_{j \neq i} w_i w_j \sigma_{ij}\end{aligned}$$

where

$\sigma(x)$ is the total portfolio's risk

σ_i^2 is the variance of asset i

σ_{ij} is the covariance between assets i and j

Σ is the full covariance matrix

Under this risk measure, the marginal risk contribution of each asset is given by:

$$\partial_{w_i} \sigma(x) = \frac{\partial \sigma(x)}{\partial w_i} = \frac{w_i \sigma_i^2 + \sum_{j \neq i} w_j \sigma_{ij}}{\sigma(x)}$$

The total risk of the portfolio can then be expressed as the sum of its total risk contributions:

$$\sigma_w = \sum_{i=1}^{n} \sigma_i(w) = \sum_{i=1}^{n} w_i \partial_{x_i} \sigma(x)$$

where

$\sigma_i(w)$ is the risk contribution of asset i

From the above, we can define the risk parity portfolio as the one where the set of assets weights (w^*) equalize their contribution to the portfolio's risk. These weights ensure that the portfolio's risk is equally balanced across all its assets. This is a non-convex, constrained quadratic programming problem that can be written as:

$$w^* = \{w \in [0,1]^n : \sum w_i = 1, w_i \partial_{w_i} \sigma(w) = w_j \partial_{w_j} sigma(w) \vee i, j\} \tag{3.1}$$

There are more than one approaches by which we can obtain the solution to this programming problem. As an example, Maillard, Roncalli and Teleitche [12] solve it numerically using sequential quadratic programming, while Zhu, Li, and Sun [14] use a branch and bound algorithm for similar results. More recently, genetic algorithms have been employed to solve these types of non-convex portfolio problems. Ardia et al. [15], building on the work of Storn and Price [16], provide an attractive solution to the problem in the form of DEoptim, a differential evolution algorithm. We use this last algorithm to solve for our portfolio's weights.

More specifically, we apply calendar dates as trading signals, and compute the portfolio's optimal weights (order sizes) using the R PortfolioAnalytics' library DEoptim solver. The trading signals are fixed dates that correspond to the last trading day of each month. On those days, the trading signals trigger the optimization procedure to solve for the optimal asset weights.

An important distinction between the risk parity strategy presented here, and the traditional implementations of these portfolios, is that we apply sequential optimizations to arrive at our optimal weights. First, we compute the risk parity weights only for assets within an asset class (equity, fixed income, commodity). Then, using those weights, we create asset class specific sub-portfolios whose return series are used as a baseline to optimize the portfolio's weights across asset classes. The optimal weights are then obtained by backtracking their values from each optimization step.

As outlined in this section, we specify the risk measure in the objective function to be the standard deviation (variance). As DEoptim is a stochastic global optimization algorithm, it can sometimes identify multiple set of weights that equalize the asset's contribution to the portfolio's risk. As such, we add to the objective function that the selected weights minimize the portfolio concentration in any one asset. This last criterion is coherent with the hybrid properties of risk parity portfolio's [12]. All of the model's parameters are estimated over a 252 days rolling window period and, we allow for the presence of leverage in the final weights. This last condition is often necessary to obtain "true" risk parity weights. The total portfolio exposure can be over or under invested to 125% and 50% within asset classes and 150% and 50% across asset classes. The code below provides some insights our specification of the problem. The reader should note that this code is used for the "within asset class" optimization of equity assets:

```
# Equity futures returns
returns.eq        <- na.omit(Return.calculate(symbols.closeprice[, symbols.eq]))
returns.eq.sma  <- na.omit(as.xts(x = (apply(X = returns.eq, FUN = "SMA", n = 2, MARGIN = 2)),
      order.by = index(returns.eq)))

# Objective function
rp.eq <- portfolio.spec(assets  = colnames(returns.eq.sma))
rp.eq <- add.objective(portfolio = rp.eq, type = "risk_budget", name = "StdDev", min_concentration =
      TRUE, min_difference = TRUE)

# Constraints
rp.eq <- add.constraint(portfolio = rp.eq, type = "box", min = 0.00, max = 1.00)
rp.eq <- add.constraint(portfolio = rp.eq, type = "leverage", min_sum = 0.50, max_sum = 1.25)

# Optimize
set.seed(1234)
opt  <- optimize.portfolio.rebalancing(R = returns.eq.sma, portfolio  = rp.monthly, optimize_method =
      "DEoptim", search_size = 5000, itermax = 50, rebalance_on = "months", trailing_period = 252,
      training_period = 252)
```

LISTING 3.1: Risk Parity - Within Asset Class (Equity) Code

The figure below presents the cumulative returns of the within asset classes sub-portfolios. The equity risk parity sub-portfolio, whose optimal weights in time are derived from the code above, is the line in pink. Even though those results are obtained for the sole purpose of computing the portfolio's weights, they include transactions costs (1bps) and a full day of slippage.

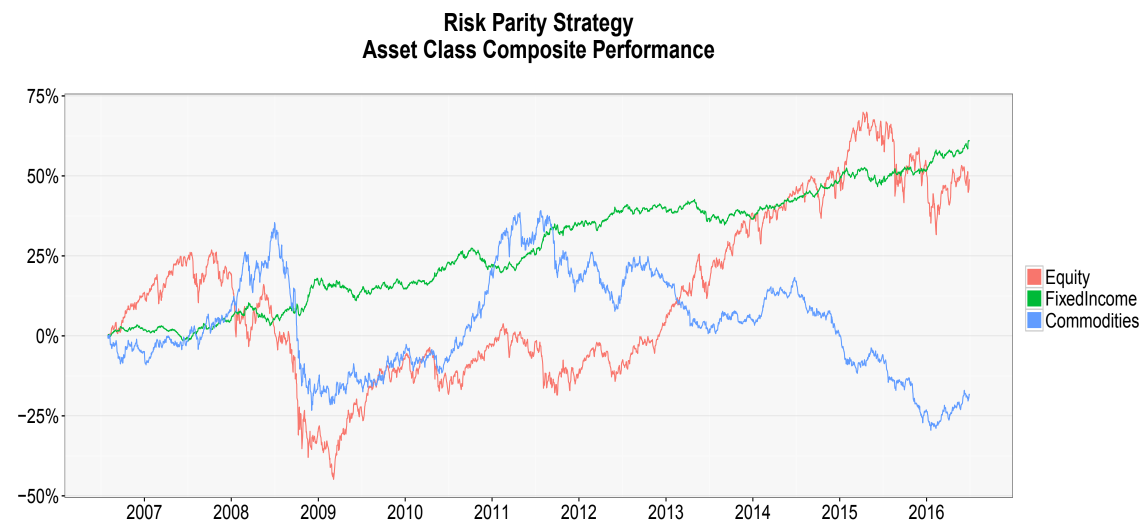

FIGURE 3.1: Risk Parity Strategy - By Asset Class Performance

3.4 Strategy Implementation

The strategy's weights are updated on a monthly basis, but we tested the impact of different rebalancing periods on the strategy's returns. As with all our backtests, we simulated realistic conditions by applying transactions of 1bps and a full day of slippage to each trade. The results are presented below.

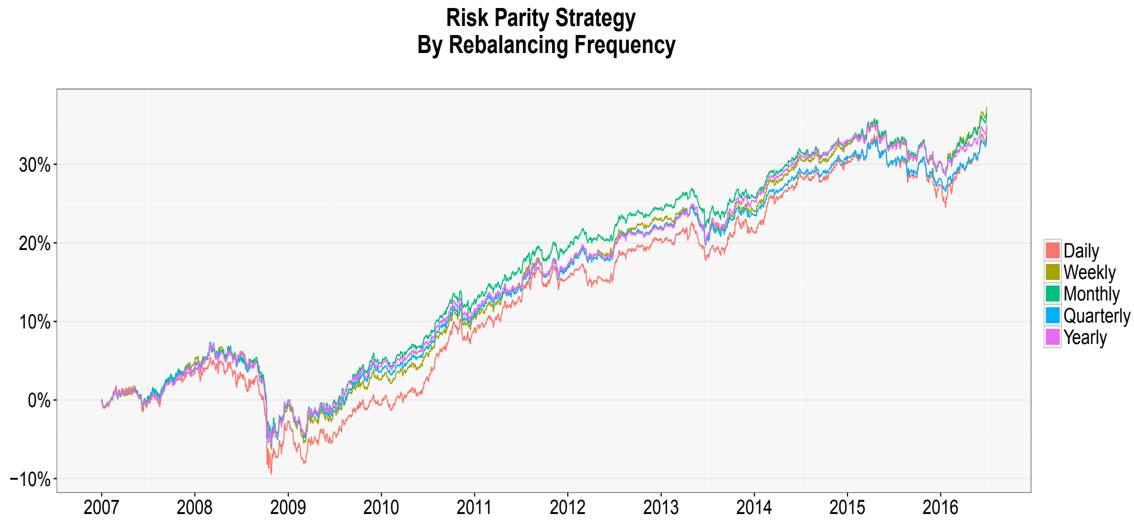

FIGURE 3.2: RiskParity Strategy - Trading Frequency

	Daily	Weekly	Monthly	Quarterly	Yearly
Cumulative Return	0.35	0.37	0.36	0.34	0.35
Annualized Return	0.03	0.03	0.03	0.03	0.03
Annualized Standard Deviation	0.04	0.04	0.03	0.03	0.03
Annualized Sharpe Ratio (rf=0%)	0.73	0.91	0.93	0.88	0.91
Worst Drawdown	0.14	0.12	0.11	0.12	0.12
Average Drawdown	0.01	0.01	0.01	0.01	0.01
Skewness	-0.63	-0.84	-0.53	-0.63	-0.57
Kurtosis	10.21	13.58	9.37	9.26	8.18

TABLE 3.2: Risk Parity Strategy - Trading Frequency

An examination of the data reveals that, in the presence of trading costs, the strategy's Sharpe ratio varies significantly. There is a full 0.20 difference in Sharpe ratio between implementing this strategy with daily and monthly trading. The cumulative returns reveals that, rebalancing on a weekly basis, dominates the other frequencies. Surprisingly, quarterly and yearly rebalanced portfolios performed similarly to others. This can be explained by the low turnover and relative weights stability inherent to the risk parity framework. Because of the small difference in Sharpe Ratio and, because of it's overall total return, we favour rebalancing the portfolio on a weekly basis.

Using our selected portfolio, we then tested for the impacts that different transactions costs may have on it. The same portfolio was implemented for trading costs ranging from zero to 25bps, with increments of 5bps. We present their performance statistics below:

	0.00%	0.05%	0.10%	0.15%	0.20%	0.25%
Cumulative Return	0.40	0.37	0.34	0.31	0.29	0.26
Annualized Return	0.03	0.03	0.03	0.03	0.03	0.02
Annualized Standard Deviation	0.03	0.03	0.03	0.03	0.03	0.03
Annualized Sharpe Ratio (rf=0%)	0.98	0.92	0.86	0.80	0.73	0.67
Worst Drawdown	0.11	0.11	0.12	0.12	0.12	0.12
Average Drawdown	0.01	0.01	0.01	0.01	0.01	0.01
Skewness	-0.51	-0.53	-0.54	-0.55	-0.56	-0.57
Kurtosis	9.35	9.34	9.32	9.29	9.26	9.23

TABLE 3.3: Risk Parity Strategy - Trading Costs

3.5 Performance Metrics

We conclude this chapter by presenting the final strategy's performance relative to a long-only equal weighted benchmark portfolio of its assets. We backtested the benchmark similarly to the strategy; within an asset class, the instruments were equally weighted to create sub-portfolios. These portfolios were then equal weighted again to obtain the final asset weights. The benchmark is rebalanced daily, at no transaction costs. This is by choice.

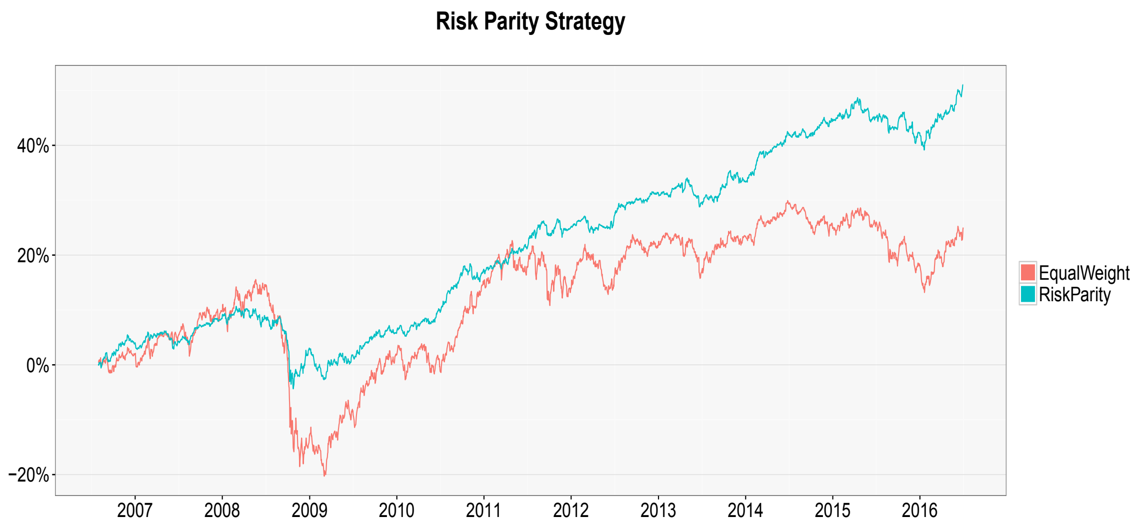

FIGURE 3.3: RiskParity Strategy - Performance

The risk parity portfolio clearly outperforms its equal weighted counterpart over the backtested period. A visual examination of both return lines reveal that the risk parity strategy had a smaller drawdown during the 2008 global financial crisis than the benchmark. Through compounding, the strategy ends up delivering a total return that far exceeds the benchmark. However, what is really impressive is the fact that the strategy's volatility is half that of the benchmark and, that its annualized return is double. Accordingly, its Sharpe ratio is almost 3 times higher than an equal weighted portfolio; a significant improvement.

	EqualWeight	RiskParity
Cumulative Return	0.25	0.51
Annualized Return	0.02	0.04
Annualized Standard Deviation	0.08	0.04
Annualized Sharpe Ratio (rf=0%)	0.27	0.98
Worst Drawdown	0.31	0.14
Average Drawdown	0.02	0.01
Skewness	-0.71	-0.60
Kurtosis	9.03	9.95

TABLE 3.4: Risk Parity Strategy - Performance Statistics

Chapter 4

Value Strategy

4.1 Literature Review

Perhaps one of the most studied risk premia, value strategies are linked to the phenomenon whereby asset prices tend to revert to their intrinsic (or otherwise fair) value. This risk premia was the subject of Graham and Dodd's seminal book [17], and ever since its publication, the equity value premium has been validated by numerous subsequent research papers. One of them is by Fama and French in 1993 [18]. In this paper, the authors demonstrate the evidence of a strong value premium in U.S. stocks, as defined by high book to market value, earnings to price, or cashflow to price ratios. Similar findings on the equity value premium were also subsequently reported by Lakonishok [19] and Fama and French [20] soon after.

The value risk premium is however not confined to equities. All major asset classes have a tendency to mean revert around fundamental value metrics, especially when their levels appear "cheap" or "rich". In the currency market for instance, it was shown that the metric, known as the purchasing power parity (PPP), explained value premia. This was first documented in the 70's in a paper by Frenkle [21]. However, this asset class' risk premium was the subject of a lot less research efforts than its equity counterpart for many years. Only recently have academics and market practitioners begun researching it again. Asness, Moskowitz and Pedersen [22] are among them. They showed that 5 years average real interest rates serve as a good baseline metric to explain exchange rates excess returns relative to one another. Similar finding by Kroencke, Schindler, and Schrimpf in 2011 [23], and later by Menko, Sarno, Schmeling and again Schrimpf in 2015 [24] corroborate this risk premium's existence.

In the fixed income markets, evidences of the value premia were also observed by Asness, Moskowitz and Pedersen [22] by using the past five year return as a valuation metric. In an industry paper, Natividade et al. [25] successfully used the term structure of interest rates to build a value metric and trade on it. Others, like Cochrane and Piazessi [26], went as far as using the interest rates' term structure's convexity as a value metric. Even though there exists strong proof of the existence of this risk premium, we failed at replicating these author's results. Our absence of success might be explained by the fact that we tried applying these metrics with futures contracts. Nevertheless, it remains that we have not succeeded in developing an acceptable risk premium harvesting strategy for this asset class. As such, we opted to entirely exclude this asset class from our value risk premia portfolio.

As for commodities, there exists anecdotal evidence that fundamental commodities trader have long dominated the physical commodities markets by trading using a broad set of value metrics. These metrics are often based on granular supply and demand data that is difficult to collect. Such data, is more often than not, impossible to collect for asset managers. To make matters even more difficult, commodities are a diverse asset class. As such, they lack universal endogenous characteristics by which they can be evaluated cross-sectionally. Because of these difficulties, we need to resort to "hacks" in order to come up with a value metric for this asset class. Asness, Moskowitz and Pedersen [22] propose one such trick by using the 5 year cumulative returns of commodity contracts as a baseline to construct a mean reverting signal. Variations around this metric serve as the basis for many commodity value strategies today.

4.2 Investment Universe

The table below lists the instruments covered by this strategy. Since we haven't managed to efficiently isolate the value risk premia strategy for fixed income futures, we omitted this asset class.

Ticker	Bloomberg Code	Description	Asset Class	Currency
ES1	ES1 Index	E-mini S&P 500 Future	Equity	USD
NK1	NK1 Index	Nikkei 225 Index Future	Equity	JPY
VG1	VG1 Index	Euro STOXX 50 Index Future	Equity	EUR
PT1	PT1 Index	S&P Toronto 60 Future	Equity	CAD
XP1	XP1 Index	ASX SPI 200 Future	Equity	AUD
CL1	CL1 Comdty	Crude Oil Future	Commodity	USD
GC1	GC1 Comdty	Gold Future	Commodity	USD
HG1	HG1 Comdty	Copper Future	Commodity	USD
NG1	NG1 Comdty	Natural Gas Future	Commodity	USD
LC1	LC1 Comdty	Live Cattle Future	Commodity	USD
S_1	S 1 Comdty	Soybean Future	Commodity	USD
W_1	W 1 Comdty	Wheat Future	Commodity	USD
C_1	C 1 Comdty	Corn Future	Commodity	USD
AD1	AD1 Curncy	AUD/USD Future	FX	USD
JY1	JY1 Curncy	JPY/USD Future	FX	USD
BP1	BP1 Curncy	GBP/USD Future	FX	USD
EC1	EC1 Curncy	EUR/USD Future	FX	USD
CD1	CD1 Curncy	CAD/USD Future	FX	USD
NV1	NV1 Curncy	NZD/USD Future	FX	USD
PE1	PE1 Curncy	MXN/USD Future	FX	USD

TABLE 4.1: Value Strategy - Investment Universe

4.3 Signals & Order Sizing

This strategy's trading signals are based on a fair value assessment of each instrument based on a fundamental metric. The value signals are constructed specifically for each asset classes. Within a given asset class, each instrument's value metric readings are ranked. This ranking is used to derive the instruments' portfolio weights. The asset class sub-portfolios implement long-short positions, and are dollar neutral. We present the signals construction methodologies below and conclude this section by outlining the exact weighting function.

4.3.1 Equity Signals

Our equity value signals are derived from Natividade's fair value strategy template [25]. Two indicators are involved in the signal's construction: the earnings yield, and the equity risk premium. We describe them below:

The Earnings Yield corresponds to the inverse of the equity index's price to earnings ratio. We use Bloomberg's earnings estimates which are derived from a 12 months trailing window of the earnings per share before accounting for extraordinary items.[1]

The Equity Risk Premium corresponds to the earnings yield (as described above) minus the 10 years swap rate of the index's country.[2]

The figures below illustrate the indicators' evolution for the strategy's equity instruments:

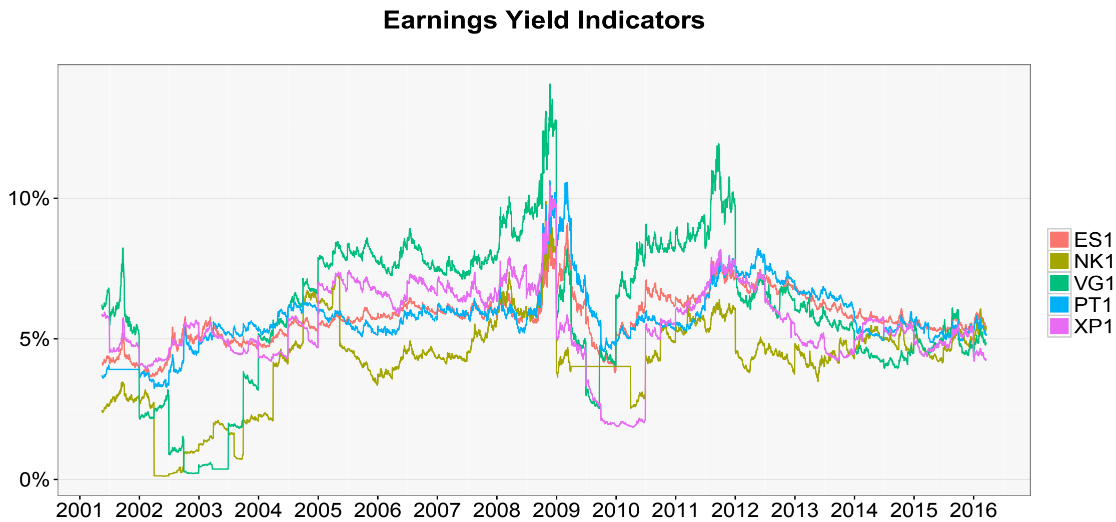

FIGURE 4.1: Value Strategy - Earnings Yield Indicators

[1]Which are obtained from the command PE RATIO in the terminal.

[2]Some authors also substract the breakeven inflation rates to the previous terms. We chose not to use it as reliable data is difficult to obtain for certain countries.

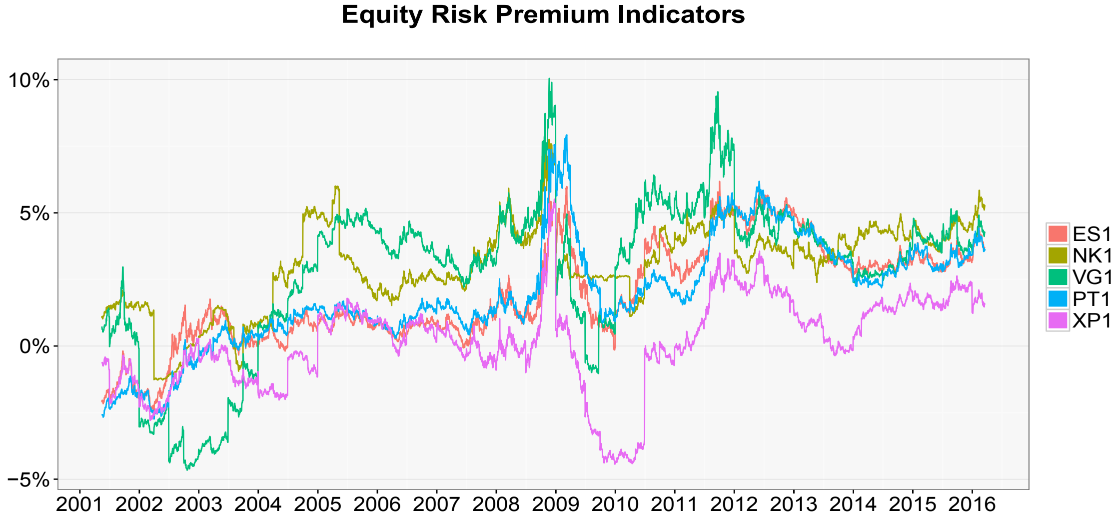

FIGURE 4.2: Value Strategy - ERP Indicators

Both indicators are ranked and converted to target weights using the order sizing function defined in section 4.3.4. The final instrument exposures are obtained by averaging both target weights.

4.3.2 FX Signals

The value signals for currency instruments are derived from a purchasing power parity (PPP) based metric. Traditional PPP metrics seek to explain the exchange rate differentials between two currencies through long-run inflation differentials. Over time, the relative value of two currencies should adjust itself so that the price of goods in one country are similar to those of the other, once accounting for exchange rate differentials. Although this dynamic generally tends to hold, many long-term deviations from PPP have been documented throughout the years. In most cases, these exchange rates misalignments can be explained by the "Penn effect"[3], and can be corrected using productivity differentials. Our indicator accounts for such effects. Its construction is as follows:

1. For each currency pair, we retrieve its country's OECD PPP rates estimates[4];
2. We then retrieve its country's World Bank GDP per capita, based on purchasing power parity estimates[5], and divide it by the equivalent US' GDP value;
3. Then, we compute the PPP implied currency exchange rates (1 / PPP) and adjust it by the GDP adjustment ratio (obtained on step 2.).
4. Finally, we calculate the percent differentials between the 30 days EMA of the exchange rate and that of the adjusted PPP implied value.

As for equity instruments, the indicator's values are ranked and converted into long-short market exposures using the strategy's order sizing methodology. The indicator's time series is presented here for illustrative purposes.

[3] We refer the reader to Stopler's [27]'s treatment of the subject.
[4] Bloomberg terminal command: PPP US Index, PPP FR Index, etc.
[5] Bloomberg terminal command: PPPGGDUS Index.

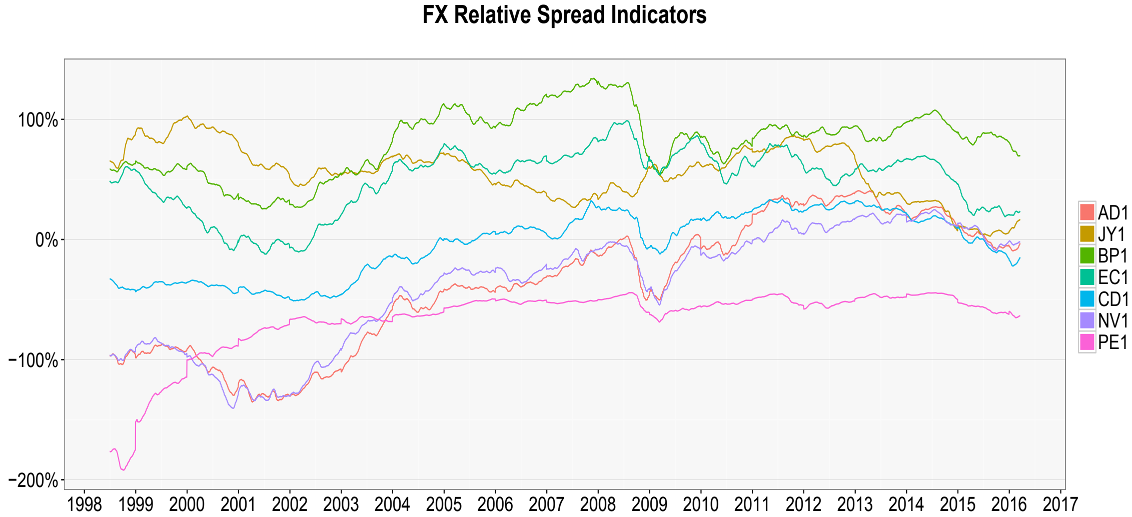

FIGURE 4.3: Value Strategy - PPP Indicators

4.3.3 Commodity Signals

Our final value risk premium signals are applied to commodity instruments. For this asset class we used a variation of Asness, Moskowitz, and Pedersen's value indicator [22]. Like them, we calculate the 5 years difference of the log returns of each instrument. Then, we filter the values by applying a simple 30 days moving average. We smooth the 5 years return to increase the indicator's stability, and ultimately limits the strategy's turnover. These simple, albeit effective, trading signals are depicted here :

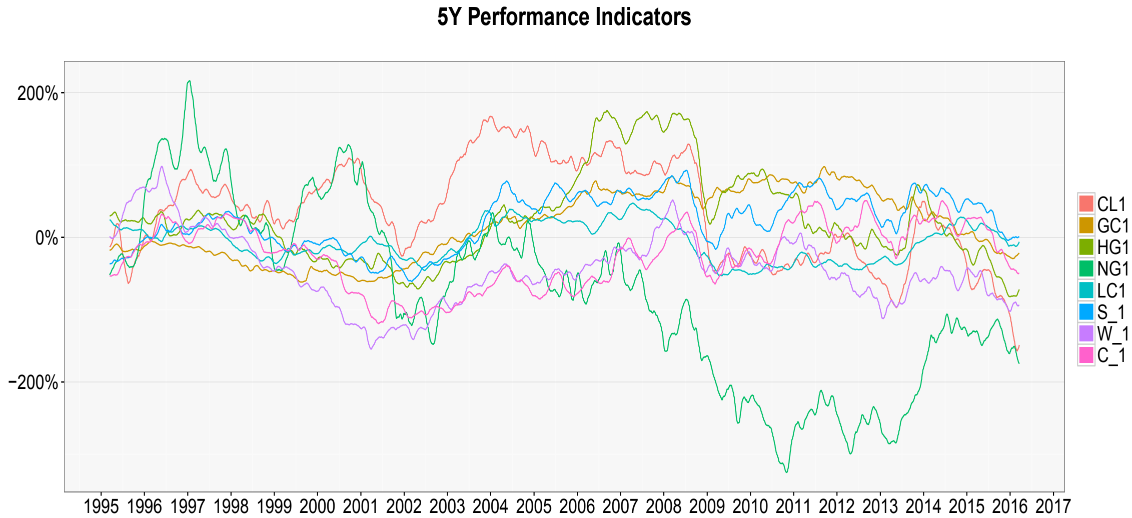

FIGURE 4.4: Value Strategy - 5Y Returns Indicators

4.3.4 Order Sizing

As previously mentioned, within each asset classes, the value strategies are dollar-neutral. This means that, for a given asset class signal, we rank its values and target a long exposure to the instruments whose signals are ranked the highest, and short those whose signals are the lowest. The higher a signal ranks, the bigger the instrument's portfolio weight (long), and vice versa.This dollar neutral weighting is the same as the one proposed by Asness, Moskowitz and Pedersen [22]. The exact weight target for an instrument i, at time t, corresponds to:

$$w_t^i = z_t(rank(I_t^i) - \frac{N_t + 1}{2} \tag{4.1}$$

where

I is the security i's fair value indicator at time t

N is the number of instruments at time t

z is a scalar that ensures the sum of the long and short exposures equal 1 and -1

4.4 Strategy Implementation

For each asset class, we rank the signals and derive their instruments weights. These target weights are lagged by one day to account for the transaction slippage. From these weights, we generate three composite sub-portfolios. One for each asset type. These return streams will be used in determining the relative weight assigned to each sub-portfolio as part of the strategy. The following figure and table contain the cumulative returns, and performance statistics of these sub-portfolios:

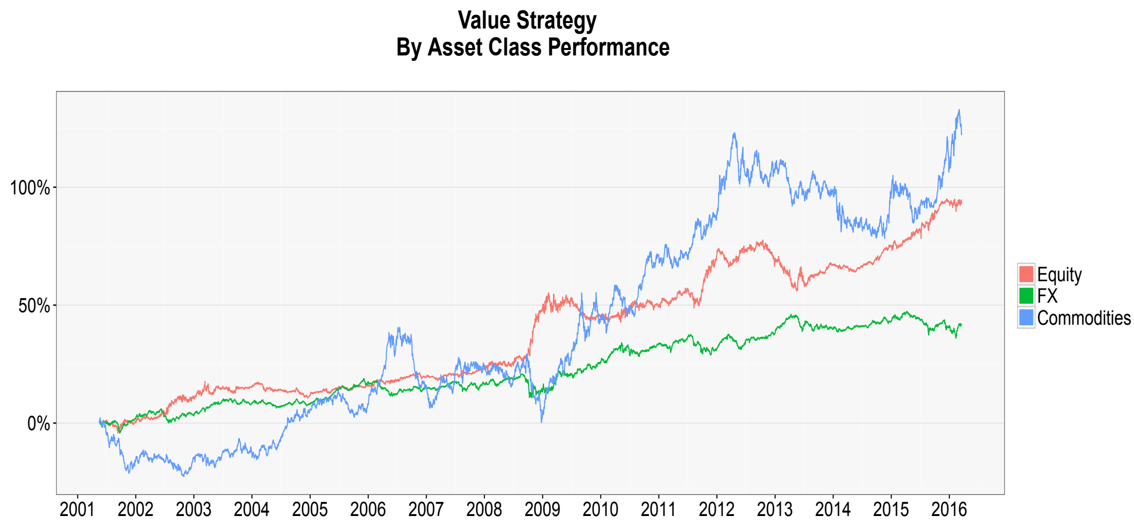

FIGURE 4.5: Value Strategy - By Asset Class Performance

	Equity	FX	Commodities
Cumulative Return	0.93	0.42	1.23
Annualized Return	0.04	0.02	0.05
Annualized Standard Deviation	0.08	0.05	0.12
Annualized Sharpe Ratio (rf=0%)	0.58	0.51	0.44
Worst Drawdown	0.12	0.08	0.29
Average Drawdown	0.01	0.01	0.03
Skewness	0.66	-0.44	-0.13
Kurtosis	10.04	8.29	4.17

TABLE 4.2: Value - Strategy By Asset Class Performance

The weights assigned to each sub-portfolio correspond to those equalizing the risk contribution of each asset class composite to that of the final portfolio. This allocation problem is the same as the one specified in Chapter 3. The only difference in this case relates to the sum of weights which are constrained to 100% (w.sum.max = 1.00). We perform the optimization and update the weights on a monthly frequency. This has no impact on the total portfolio trading frequency (which is presented later). The exact optimization parameters are:

```
Weights.ERC(returns = foo.data,
        rebalancing.frequency   = "months",
        optimization.type              = "risk_budget",
        objective . function             = "StdDev",
        w.min                          = 0.00,
        w.max                          = 1.00,
        w.sum.min                      = 0.99,
        w.sum.max                      = 1.01,
        training . period              = 90,
        trailing . period              = 90)
```

LISTING 4.1: Value Strategy - Composite Weights Code

Using the composite weights, we backtracked each instrument exposures. To assess the impact of the rebalancing frequency on the strategy, we backtested five portfolios (daily, weekly, monthly, quarterly, and yearly). For each backtest, we accounted for a full day of slippage, and 1bps of transaction costs. The strategy's returns present a relatively similar profile at all time-frames but, longer rebalancing time-frames clearly dominate the shorter ones. The yearly rebalanced strategy has the highest Sharpe ratio, followed by the monthly and weekly ones.

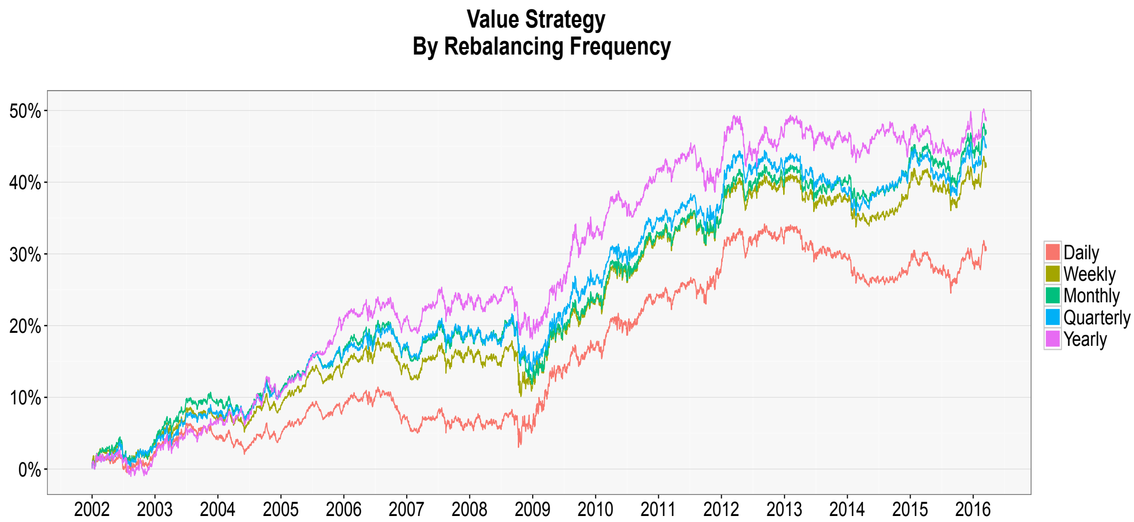

FIGURE 4.6: Value Strategy - Trading Frequency

	Daily	Weekly	Monthly	Quarterly	Yearly
Cumulative Return	0.30	0.42	0.47	0.45	0.49
Annualized Return	0.02	0.02	0.03	0.03	0.03
Annualized Standard Deviation	0.04	0.04	0.04	0.04	0.04
Annualized Sharpe Ratio (rf=0%)	0.43	0.54	0.60	0.58	0.63
Worst Drawdown	0.08	0.07	0.08	0.07	0.06
Average Drawdown	0.01	0.01	0.01	0.01	0.01
Skewness	0.01	-0.15	-0.11	-0.17	-0.28
Kurtosis	6.46	6.06	5.01	4.81	4.75

TABLE 4.3: Value Strategy - Trading Frequency

Even if the yearly rebalancing policy dominates all others, we opted to implement the final strategy with weekly rebalancings. Should the strategy's signals become more volatile in the future, rebalancing the portfolio on a weekly basis would ensure that we capture the changes in exposures that arise from this. The performance differences between weekly and monthly rebalancing's aren't enough, in our opinion, to justify rebalancing only on a monthly frequency.

Testing for the impact of transaction costs, we can see from the table below that, for transaction costs that are above 0.10%, the strategy's attractiveness quickly deteriorates. Above this level, the portfolio's Sharpe ratio quickly diminishes below 0.50 which, for a long-short portfolio, is average at best.

	0.00%	0.05%	0.10%	0.15%	0.20%	0.25%
Cumulative Return	0.57	0.50	0.44	0.38	0.33	0.27
Annualized Return	0.03	0.03	0.02	0.02	0.02	0.02
Annualized Standard Deviation	0.04	0.04	0.04	0.04	0.04	0.04
Annualized Sharpe Ratio (rf=0%)	0.69	0.62	0.56	0.49	0.43	0.36
Worst Drawdown	0.07	0.07	0.07	0.08	0.08	0.09
Average Drawdown	0.01	0.01	0.01	0.01	0.01	0.01
Skewness	-0.15	-0.15	-0.14	-0.14	-0.14	-0.14
Kurtosis	6.00	6.01	6.02	6.02	6.03	6.03

TABLE 4.4: Value Strategy - Trading Costs

4.5 Performance Metrics

The final strategy's backtest is presented relative to a long-only benchmark composed of the same instruments it trades. The benchmark is an equal weighted portfolio of the asset classes composites where each asset class sub-portfolio is equally weighted across its instruments. The chart below illustrates the appeal of alternative risk premia strategies relative to traditional risk premia. The value strategy's performance is much more stable than its counterpart, suffers significantly smaller drawdowns, and realizes a similar annualized return. As is the case for most alternative risk premia, over the backtest period, it realizes an attractive 0.68 annualized Sharpe ratio. This is twice the expected return per volatility unit of the benchmark. Given the long backtest period, we are confident that these results were obtained throughout a full, albeit turbulent business cycle. We omit their presentation, but the p-values of our Sharpe ratio estimates are well below 0.05, further reinforcing our robustness claim.

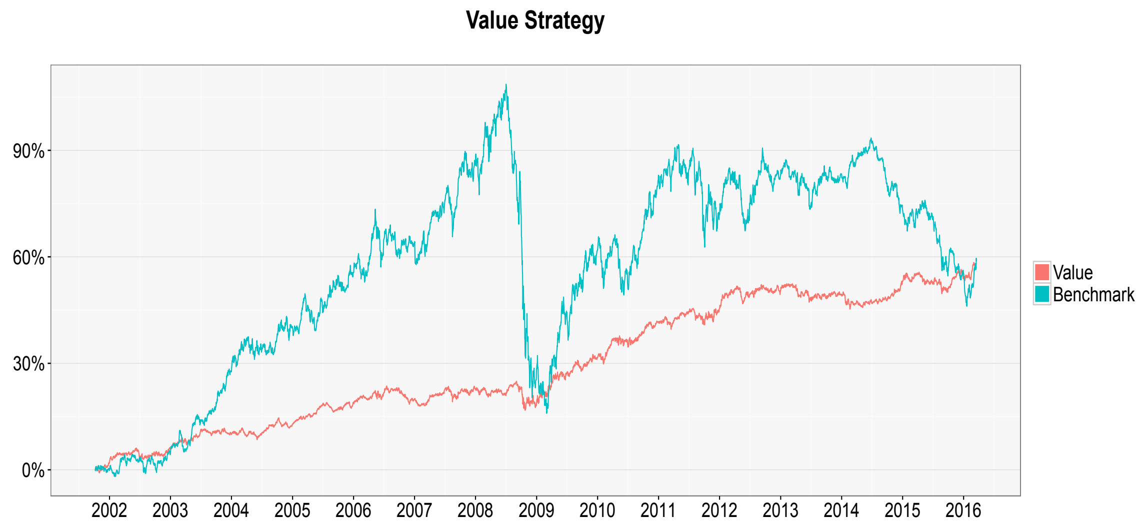

FIGURE 4.7: Value Strategy - Performance

	EqualWeight	RiskParity
Cumulative Return	0.25	0.51
Annualized Return	0.02	0.04
Annualized Standard Deviation	0.08	0.04
Annualized Sharpe Ratio (rf=0%)	0.27	0.98
Worst Drawdown	0.31	0.14
Average Drawdown	0.02	0.01
Skewness	-0.71	-0.60
Kurtosis	9.03	9.95

TABLE 4.5: Value Strategy - Performance Statistics

Chapter 5

Carry Strategy

5.1 Literature Review

The carry risk premia has long been exploited in almost every asset classes by investors and speculators alike. A generalized interpretation of what carry is can be found in Koijen, Moskowitz, Pedersen and Vrugt's seminal paper titled "Carry" [28]. Carry is essentially the expected return from an asset, assuming its price remains the same over a certain period of time. This makes it unique among alternative risk premia because its expected return can be estimated prior to its realization. Indeed, Moskowitz's describes carry as "a model-free characteristic that is directly observable ex ante.". This makes carry a generic proxy for the broad market risk premium; it makes sense as carry essentially represents the minimal return that the market participants require to invest in a security.

Currency carry trades were documented as early as 1981 by Bilson [29], followed by Messe and Rogoff in 1983 [30], and Fama in 1984 [31]. It is well accepted that, unlike most financial assets, the currency markets do not reward an investor with a holding benefit. Carry strategies present a way to extract a risk premium from this market. The return characteristics of currency carry strategies is studied in detail in a working paper by Burnside [32]. His paper establishes the attractiveness of such strategies over multiple business cycles, thus validating the very existence of this risk premium for this asset class[1].

In commodities, the carry risk premium is a function of the term structure dynamics. In 1930, Keynes proposed that the backwardation, observed in commodities term structures, arises from inventory and price risk dynamics between producers and speculators [33]. This can be exploited by investors to generate returns. Following Keynes' research, Kaldor [34], Cootner [35], and more recently Rouwenhorst [36] improved on Keyne's findings by identifying different explanatory factors explaining commodity returns. Based on these, Koijen, Moskowitz, Pedersen and Vrugt [28] proposed a commodity strategy that harvests this asset class' carry dynamics. Ahmerkamp and Grant also came up with a similar strategy that same year [37].

The risk premium existence was also validated in the equity and global bond markets. It was demonstrated that yield spreads are a predictor of bond returns by many authors [38] [39], and that they could be used to harvest carry returns [28]. In the equity markets, the dividend yield is a predictor of an equity index future's returns, and can be used to harvest a global equity carry risk premium [28]. We have tried replicating the

[1] An important result of this paper is that it rejects the assumptions made under the uncovered interest rate parity models.

baseline results from the cited works, but failed at obtaining results that were satisfactory. As such, we focused our carry strategy research on commodities and currencies exclusively.

5.2 Investment Universe

The table below lists the futures instruments transacted as part of these strategies. One should note that we only had access to a few currency instruments; most currency trades take place in the Forward markets rather than with futures.

Ticker	Bloomberg Code	Description	Asset Class	Currency
AD1	AD1 Curncy	AUD/USD Future	FX	USD
BP1	BP1 Curncy	GBP/USD Future	FX	USD
CD1	CD1 Curncy	CAD/USD Future	FX	USD
EC1	EC1 Curncy	EUR/USD Future	FX	USD
JY1	JY1 Curncy	JPY/USD Future	FX	USD
NV1	NV1 Curncy	NZD/USD Future	FX	USD
PE1	PE1 Curncy	MXN/USD Future	FX	USD
LA1	LA1 Comdty	Aluminum Future	Commodity	USD
LA2	LA2 Comdty	Aluminum Future (2nd)	Commodity	USD
HG1	HG1 Comdty	Copper Future	Commodity	USD
HG2	HG2 Comdty	Copper Future (2nd)	Commodity	USD
GC1	GC1 Comdty	Gold Future	Commodity	USD
GC2	GC2 Comdty	Gold Future (2nd)	Commodity	USD
SI1	SI1 Comdty	Silver Future	Commodity	USD
SI2	SI2 Comdty	Silver Future (2nd)	Commodity	USD
CO1	CO1 Comdty	Brent Oil Future	Commodity	USD
CO2	CO2 Comdty	Brent Oil Future (2nd)	Commodity	USD
QS1	QS1 Comdty	Gas Oil Future	Commodity	USD
QS2	QS2 Comdty	Gas Oil Future (2nd)	Commodity	USD
CL1	CL1 Comdty	Crude Oil Future	Commodity	USD
CL2	CL2 Comdty	Crude Oil Future (2nd)	Commodity	USD
NG1	NG1 Comdty	Natural Gas Future	Commodity	USD
NG2	NG2 Comdty	Natural Gas Future (2nd)	Commodity	USD
CT1	CT1 Comdty	Cotton Future	Commodity	USD
CT2	CT2 Comdty	Cotton Future (2nd)	Commodity	USD
KC1	KC1 Comdty	Coffee Future	Commodity	USD
KC2	KC2 Comdty	Coffee Future (2nd)	Commodity	USD
CC1	CC1 Comdty	Cocoa Future	Commodity	USD
CC2	CC2 Comdty	Cocoa Future (2nd)	Commodity	USD
SB1	SB1 Comdty	Sugar Future	Commodity	USD
SB2	SB2 Comdty	Sugar Future (2nd)	Commodity	USD
S_1	S 1 Comdty	Soybean Future	Commodity	USD
S_2	S 2 Comdty	Soybean Future (2nd)	Commodity	USD
W_1	W 1 Comdty	Wheat Future	Commodity	USD
W_2	W 2 Comdty	Wheat Future (2nd)	Commodity	USD
C_1	C 1 Comdty	Corn Future	Commodity	USD
C_2	C 2 Comdty	Corn Future (2nd)	Commodity	USD
LH1	LH1 Comdty	Lean Hog Future	Commodity	USD
LH2	LH2 Comdty	Lean Hog Future (2nd)	Commodity	USD
FC1	FC1 Comdty	Feeder Cattle Future	Commodity	USD
FC2	FC2 Comdty	Feeder Cattle Future (2nd)	Commodity	USD
LC1	LC1 Comdty	Live Cattle Future	Commodity	USD
LC2	LC2 Comdty	Live Cattle Future (2nd)	Commodity	USD

TABLE 5.1: Carry Strategy - Investment Universe

5.3 Signals & Order Sizing

Regardless of asset class, all carry trading signals are based on an assessment of an "assets expected return assuming that market conditions, including its price, stays the same." [28]. Any security's return can therefore be explained by a carry return component and a price appreciation return component:

$$R_{t,T} = C_{t,T} + E(P_T - P_t) + \varepsilon \tag{5.1}$$

where

$R_{t,T}$ is the asset's total return between time t T
$C_{t,T}$ is the asset's carry return between time t T
$E(P_T - P_t)$ is the expected price appreciation of the asset between time t and T
ε is the asset's unexpected price movements

For a fully collateralized future's trade, the carry return component can be expressed as:

$$C_{t,T} = \frac{S_t - F_{t,T}}{F_{t,T}} \tag{5.2}$$

where

$C_{t,T}$ is the asset's carry at time t
S_t is the asset's spot price at time t
$F_{t,T}$ is the asset's futures contract price (with maturity T) at time t

Using the above equation, we developed asset class specific carry signals.

5.3.1 Foreign Exchange

Our currency carry signals use the classic interest rate spread as proposed by Kroencke in 2011 [23] and later Moskowitz [28]. For a given currency futures contract, we defined the carry indicator as the spread between the interest rates of the base and term countries. Since the no-arbitrage price of a currency forward contract is a function of this interest rate spread, we can therefore infer its value directly from the FX forward premium or discount. Using a notation similar to that of Anand, et al. [40] we express the currency carry as follow:

$$F_{t,T} = S_t \frac{1 + r_{t,T}^{foreign} * \Delta_{t,T}}{1 + r_{t,T}^{local} * \Delta_{t,T}}$$

$$C_{t,T} = \frac{F_{t,T}}{S_t} - 1$$

where

$C_{t,T}$ is the instrument's carry at time t

$F_{t,T}$ is the instrument's forward price (with maturity T) at time t

$r_{t,T}^{local}$ is the local interest rate (with maturity T) at time t

$r_{t,T}^{foreign}$ is the foreign interest rate (with maturity T) at time t

It should be noted that the forward price, as described above, implies a no-arbitrage relationship between the spot price and forward price. In other words, we assume the non-violation of covered interest rate parity. Covered IRP has been empirically proven to hold for short time-frames (months), hence why we use the forward discount / premium in the construction of our carry signals. As we use futures to implement the strategy, we priviledged using the 3 months forward prices instead of the 1 month forwards traditionally used in the literature. The figure below illustrates the evolution of the different forward discounts / premiums computed for the currency instruments traded:

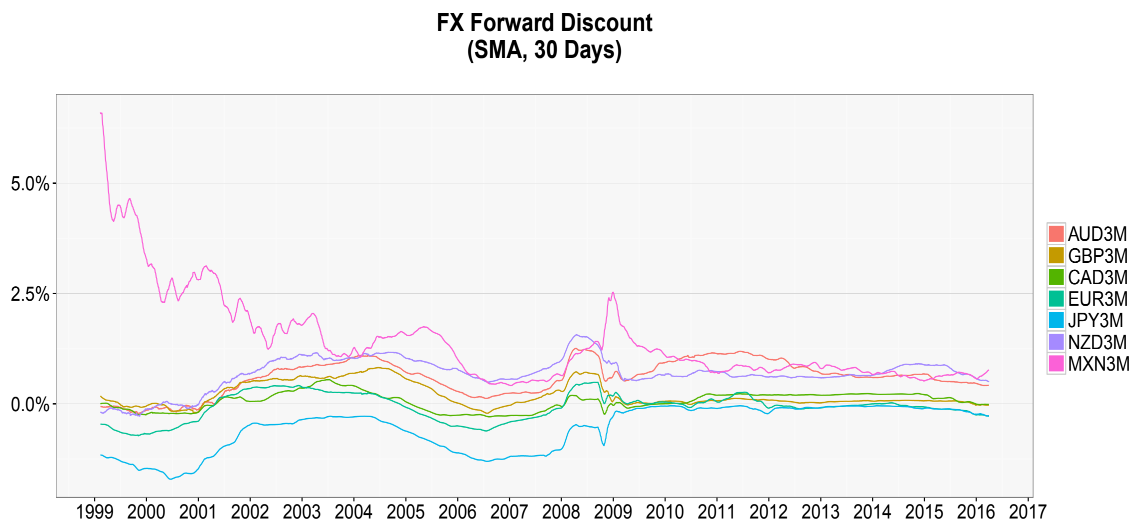

FIGURE 5.1: FX Carry Strategy - Forward Discounts

A classic carry strategy would transform the forward discounts into trading weights by implementing a dollar neutral portfolio that goes long the currency futures exhibiting the highest forward premiums, and short those exhibiting the highest forward discounts. We do the same, however we extend this signal with a reverse carry indicator. This addition is important to our strategy because, although FX carry portfolios produce significant average returns, they are extremely vulnerable to global currency shocks. Pure FX carry portfolio have therefore a tendency to suffer crash like losses. This behaviour has been thoroughly studied by Burnside [41]. These crashes are low probability extreme losses that are the result of large endogenous unwinding of speculative money[2]. Authors studying these risks found that they could be predicted by the level of FX volatility [43]. We based our research on these findings, to augment our signals with a global FX variance indicator that, when triggered, reverses our baseline carry positions. The construction of this indicator is loosely based on works from Cenedese [44] and Menkhoff [45].

Our reverse carry indicator is constructed using 33 currency pairs. For each, we compute their daily log returns, and average them over the 33 currencies used. We then square the average of the daily returns and compute their average over a month. This last value is a proxy for the global FX variance. We compute its innovations to construct the final indicator. The equations below detail the indicator's computation methodology:

$$\sigma_t^{FX} = \frac{1}{T_t} \sum_{\tau \in T_t} \left[\sum_{k \in K_\tau} \left(\frac{|r_\tau^k|}{K_\tau} \right) \right]^2$$

$$\varepsilon_t^{FX} = \varepsilon_t^{FX} - \varepsilon_{t-T_t}^{FX}$$

where

$\left|r_\tau^k\right| = |log\Delta s_\tau|$ is the k currency's instrument log return at time τ

K_τ is the number of available currencies on dayτ

T_t is the total number of trading days in a month t

The figure below presents the value in time for this variance indicator, as well as its innovations:

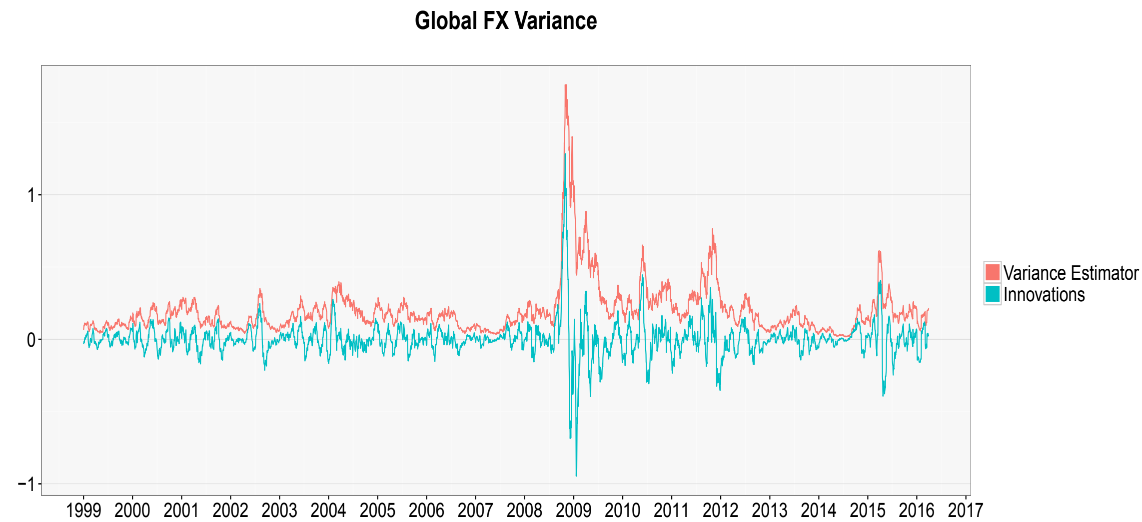

FIGURE 5.2: FX Carry Strategy - Global FX Variance

We use this particular variance estimator because it presents interesting properties. For a thorough review of them, we refer the reader to Menkhoff's work [45]. For the purpose of this paper, it suffices to say that this indicator's innovations can be used to

[2]Some authors, like Brunnermeier [42] attribute these to liquidity constraints.

construct a rolling quantile measure that will serve as a reverse carry trigger. Should the 50 days single moving average of the variance innovations exceed their 500 days rolling quantile, a signal to reverse the carry positions is received. We illustrate this below:

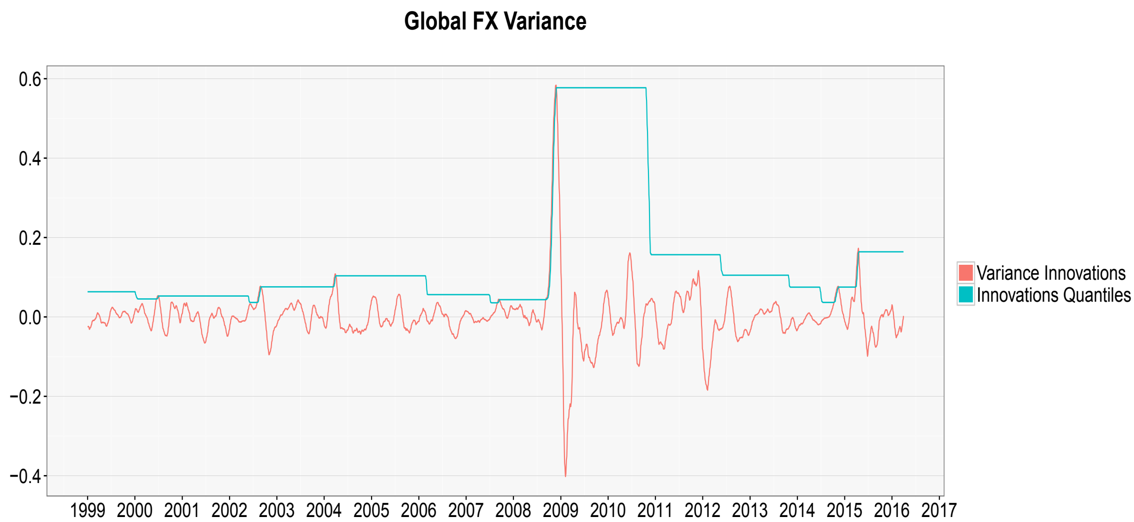

FIGURE 5.3: FX Carry Strategy - Innovations and Quantiles

Having detailed the construction of the reverse carry indicator, we can outline how we obtain the final strategy's weights. On a monthly basis we observe the following rules:

$$Signal = \begin{cases} +1, \text{ if } FwdDiscn_n >= quantile(FwdDiscn_1, ..., FwdDiscn_N)_(1 - 2/N) \geq 0 \\ -1, \text{ if } FwdDiscn_n >= quantile(FwdDiscn_1, ..., FwdDiscn_N)_(1 - 2/N) \geq 0 \\ 0, \text{ else} \end{cases}$$

where

N corresponds to the total number of currencies
$+1$ corresponds to a go long signal
-1 corresponds to a go short signal
0 corresponds to a neutral signal

This gives our baseline strategy's positioning. However, the reverse carry indicator can change that positioning at any point in time if:

$$Signal = \begin{cases} 1, \text{ if } \epsilon_t >= quantile(\epsilon_{t-\tau}, ..., \epsilon_t)_{0.99} \\ 0, \text{ else} \end{cases}$$

where

ϵ_t corresponds the variance indicator's innovations
1 corresponds to a long reverse carry signal
0 corresponds to a neutral reverse carry signal

The final strategy's order sizes consists in applying a 25% weight multiplier to the previously computed signals. Doing so implements an unlevered dollar neutral portfolio whereby in this particular case, we are long the two strongest yielding currency futures, and short the lowest two[3]. The positioning is promptly inverted in the event of a reverse carry signal.

5.3.2 Commodity

The commodity carry signals are taken directly from Koijen, Moskowitz, Pedersen and Vrugt's "Carry" paper [28]. We use their notation in the presentation of our carry indicators. Theoretically, a commodity's carry can be estimated by comparing its spot price to its first nearby futures price. This however proves difficult in practice as the commodities markets often lack reliable spot prices. A workaround consists in estimating carry from the "slope" between the first nearby and second nearby contracts. Assuming that the no arbitrage price for a specific commodity futures is:

$$F_t = S_t(1 + r_t^f - \delta_t) \tag{5.3}$$

where

F_t is the current futures price
S_t is the asset's spot price
r_t^f is the prevailing risk free rate
δ_t is the convenience yield

Then, generalizing the no-arbitrage futures price relationship, and thus assuming that the 2nd nearby contract's price will converge to the first nearby upon maturity, we obtain the following expression of carry[4]:

$$C_t = \frac{F_t^1 - F_t^2}{F_t^2(T_2 - T_1)} \tag{5.4}$$

[3]Known as the funding currencies.
[4]Most authors adjust this estimator by the time differential between both contract's maturity. They do this by dividing the equation terms by $(T_2 - T_1)$. We opt not to use this adjustment as we find it doesn't add much precision to the signals.

where

$C_{t,T}$ is the asset's carry at time t
F_t^1 is the first nearby future contract's price at time t
F_t^2 is the second nearby future contract's price at time t
T_1 is the time to maturity (in months) of the first nearby contract
T_2 is the time to maturity (in months) of the second nearby contract

The carry estimates can be extremely volatile due to daily variations in the contracts' prices, and to seasonality effects found in certain commodity term structures. Therefore, we smooth the above indicator using a rolling 252 days simple moving average. Other windows achieve the desired effect. The choice of using a full year is so that we smooth seasonal effects, while also mitigating the impact of the day to day noise on the indicator's value. The carry indicators for the different commodity instruments traded as part of the strategy are presented below:

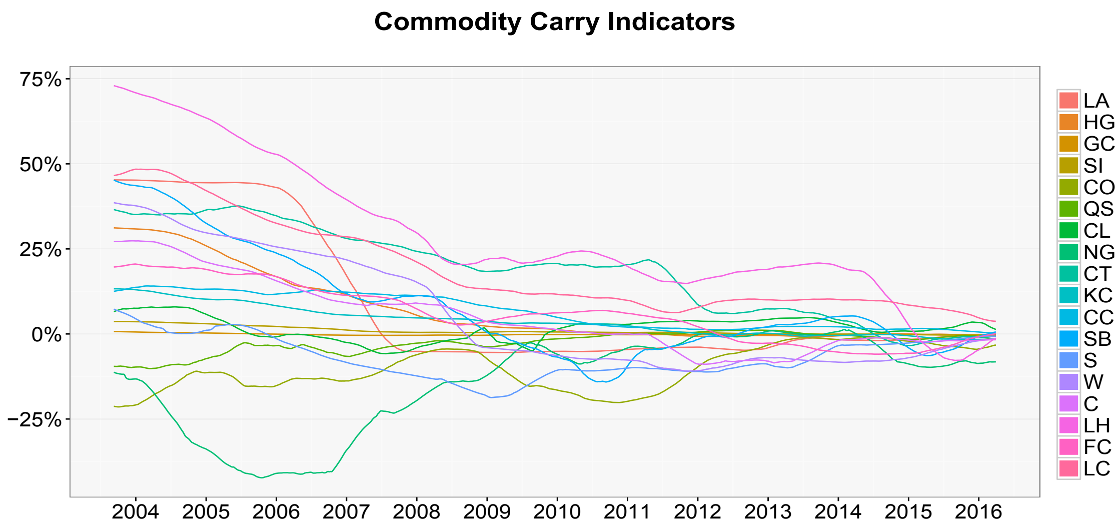

FIGURE 5.4: Commodity Carry Strategy - Roll Yield Indicators

Finally, the strategy's trading weights are derived from the indicator's ranking through the dollar neutral weighting scheme used in the value strategy. To obtain the weights, we rank the commodities carry indicators and apply the methodology proposed by Asness [22]:

$$w_t^i = z_t(rank(I_t^i) - \frac{N_t + 1}{2}) \tag{5.5}$$

where

I is the security i's carry indicator at time t
N is the number of instruments at time t
z is a scalar that ensures the sum of the long and short exposures equal 1 and -1

Note that those weights are applied to commodities. For commodities who are highly ranked[5], the weight is positive. For commodities who are lowly ranked[6] the weight is negative. To obtain the weight's allocation between the first nearby and second nearby futures, we divide the target weight by two, and allocate it to the first nearby and second nearby futures as follows: If the weight is positive, the strategy goes long the second nearby contract (by half the target weight value) and short the first nearby contract (by half the target weight value). If the weight is negative, the signs (long / short) are inverted for both contracts.

5.4 Strategy Implementation

5.4.1 Foreign Exchange

We first backtest the currency carry strategy under different rebalancing frequencies. Daily, weekly, monthly, and quarterly, rebalanced portfolios were backtested. For each, we considered a full day of slippage before each trade, and applied transaction costs of 1 basis points (per size of notional). The backtests cumulative returns, and their performance statistics are presented in the figure and table below:

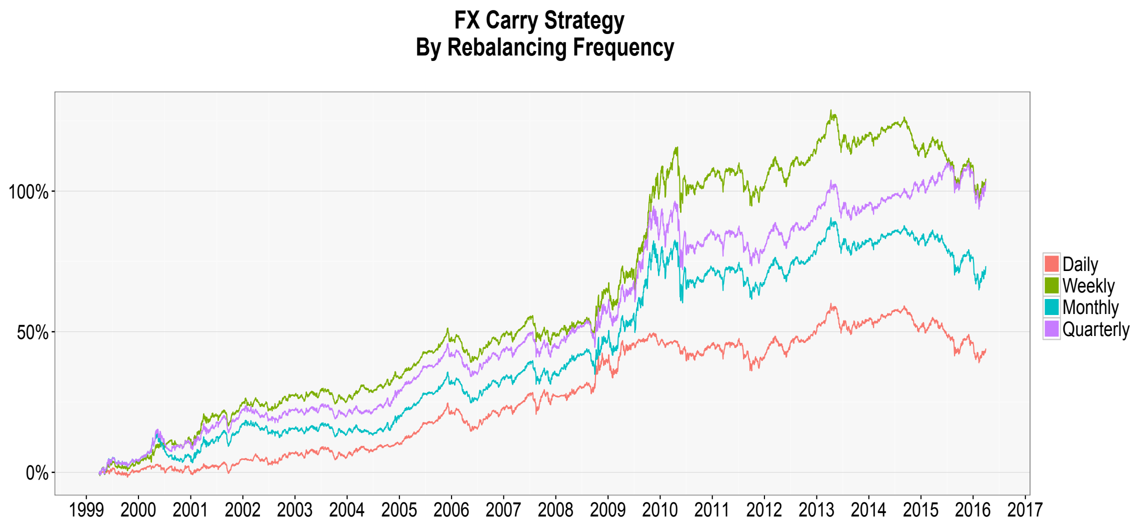

FIGURE 5.5: FX Carry Strategy - Trading Frequency

	Daily	Weekly	Monthly	Quarterly
Cumulative Return	0.44	1.04	0.73	1.03
Annualized Return	0.02	0.04	0.03	0.04
Annualized Standard Deviation	0.05	0.06	0.06	0.07
Annualized Sharpe Ratio (rf=0%)	0.43	0.67	0.49	0.63
Worst Drawdown	0.13	0.14	0.13	0.12
Average Drawdown	0.01	0.01	0.01	0.01
Skewness	-0.18	-0.00	-0.17	-0.16
Kurtosis	11.70	10.91	11.16	10.97

TABLE 5.2: FX Carry Strategy - Trading Frequency

[5] And who are most likely, but not necessarily, backwardated ($F_t^1 >= F_t^2$)
[6] And who are, most likely, but not necessarily contangoed ($F_t^1 < F_t^2$)

The above statistics identify the weekly rebalancing policy as the one resulting in a maximal Sharpe ratio for the strategy. This rebalancing frequency suffers a higher maximum drawdown (14%), but provides the most attractive total return over the backtest period. Choosing a weekly rebalancing frequency also ensures that both, the carry and reverse carry signals, are implemented as part of the portfolio. While a daily rebalancing might seem justified, especially given the use of our reverse carry indicator, its increased trading cost significantly impacts the portfolio's returns. To further assess the the performance impact of those costs, we present below the weekly rebalanced strategy's performance metrics under multiple transaction fee assumptions. These transaction costs are well above what an institutional investor should expect to pay to transact currency futures. In fact, even our baseline costs of 1 basis point are conservative.

	0.00%	0.05%	0.10%	0.15%	0.20%	0.25%
Cumulative Return	1.15	0.99	0.85	0.72	0.60	0.48
Annualized Return	0.04	0.04	0.04	0.03	0.03	0.02
Annualized Standard Deviation	0.06	0.06	0.06	0.06	0.06	0.06
Annualized Sharpe Ratio (rf=0%)	0.71	0.64	0.57	0.50	0.43	0.36
Worst Drawdown	0.14	0.15	0.15	0.15	0.15	0.15
Average Drawdown	0.01	0.01	0.01	0.01	0.01	0.01
Skewness	-0.00	0.00	0.01	0.02	0.02	0.02
Kurtosis	10.88	10.86	10.83	10.79	10.73	10.66

TABLE 5.3: FX Carry Strategy - Trading Costs

5.4.2 Commodities

We perform the same backtests on the commodity portfolio. An examination of the different backtests equity line reveals some interesting features. For one, it would seem that the strategy's total return is similar for rebalancing frequencies up to a month. At the quarterly and yearly frequencies, the cumulative return augments significantly. The increased returns however come accompanied by a lot more volatility, making these last two choices, unappealing from a Sharpe ratio perspective. The longer rebalancing frequencies clearly offer a lower return for a given unit of risk (volatility) than their daily or weekly rebalanced counterparts. As such, we select our rebalancing frequency to be weekly[7]. The figure and table below present the backtests statistics:

[7] A daily rebalancing frequency placing too heavy a burden from a trading perspective.

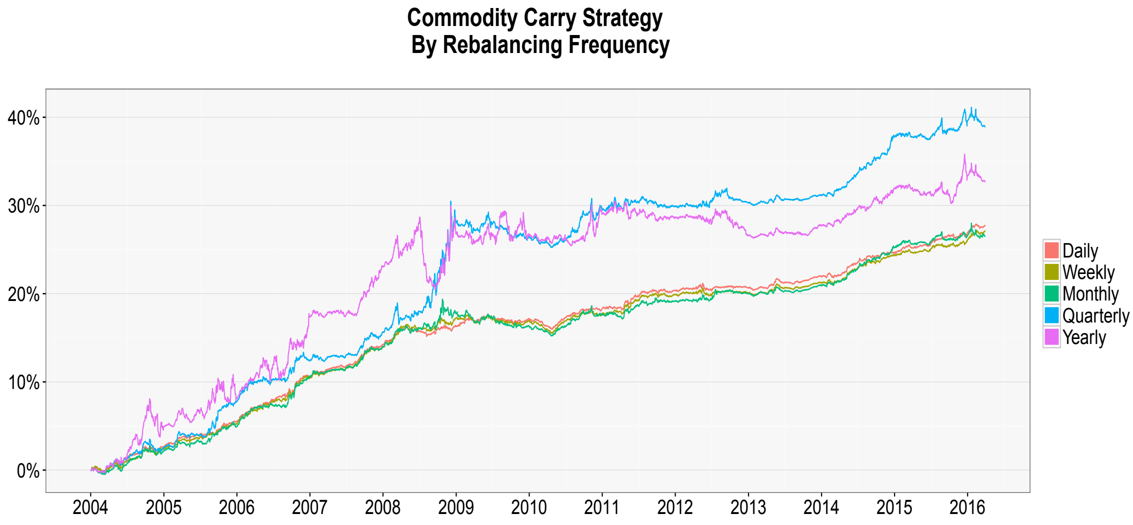

FIGURE 5.6: Commodity Carry Strategy - Trading Frequency

	Daily	Weekly	Monthly	Quarterly	Yearly
Cumulative Return	0.28	0.27	0.26	0.39	0.33
Annualized Return	0.02	0.02	0.02	0.03	0.02
Annualized Standard Deviation	0.01	0.01	0.01	0.02	0.03
Annualized Sharpe Ratio (rf=0%)	2.10	1.91	1.38	1.18	0.73
Worst Drawdown	0.01	0.02	0.03	0.04	0.06
Average Drawdown	0.00	0.00	0.00	0.00	0.01
Skewness	0.66	0.53	-0.72	-0.59	-0.25
Kurtosis	8.07	7.19	25.51	33.74	16.13

TABLE 5.4: Commodity Carry Strategy - Trading Frequency

Although we recognize that the Sharpe ratio is the highest for daily rebalancings, we feel that opting for weekly rebalancings only increases the strategy's volatility marginally. The same can also be observed for the maximum drawdown statistic. Given that the goal of this research is to develop strategies that are implementable for the largest portion of investors, we stand by our choice of a weekly rebalanced portfolio. Finally, we present the backtests for different trading costs:

	0.00%	0.05%	0.10%	0.15%	0.20%	0.25%
Cumulative Return	0.29	0.27	0.25	0.24	0.22	0.20
Annualized Return	0.02	0.02	0.02	0.02	0.02	0.01
Annualized Standard Deviation	0.01	0.01	0.01	0.01	0.01	0.01
Annualized Sharpe Ratio (rf=0%)	1.95	1.84	1.74	1.63	1.53	1.43
Worst Drawdown	0.02	0.02	0.02	0.02	0.02	0.02
Average Drawdown	0.00	0.00	0.00	0.00	0.00	0.00
Skewness	0.50	0.50	0.51	0.51	0.50	0.50
Kurtosis	7.06	7.05	7.03	7.01	6.99	6.99

TABLE 5.5: Commodity Carry Strategy - Trading Costs

5.5 Performance Metrics

This final section presents the strategies performance metrics relative to their long-only benchmarks. Unlike for the value portfolio, we do not blend both strategies together in a single portfolio. We omit to do so because there are only two asset classes in which we efficiently managed to harvest carry risk premia. The two strategies correlation is very close to zero. As such, an equal weighted portfolio of them closely approximates their equal risk contribution portfolio equivalent. We continue to research methods that would allow us to extract this risk premia in the equity and fixed income markets and, hope to present and analyze our results in a single portfolio format in our future research. The benchmark for each strategy consists in an equal weighted portfolio of its underlying instruments. We assume that they are rebalanced daily with no slippage or transaction costs.

5.5.1 Foreign Exchange

The below figure presents the FX Carry's strategy relative to its benchmark. Its equity line, albeit volatile, displays a more attractive profile than that of its benchmark. Upon closer examination, we can see the influence of the reverse carry signals in the performance between the years 2008 and 2009.

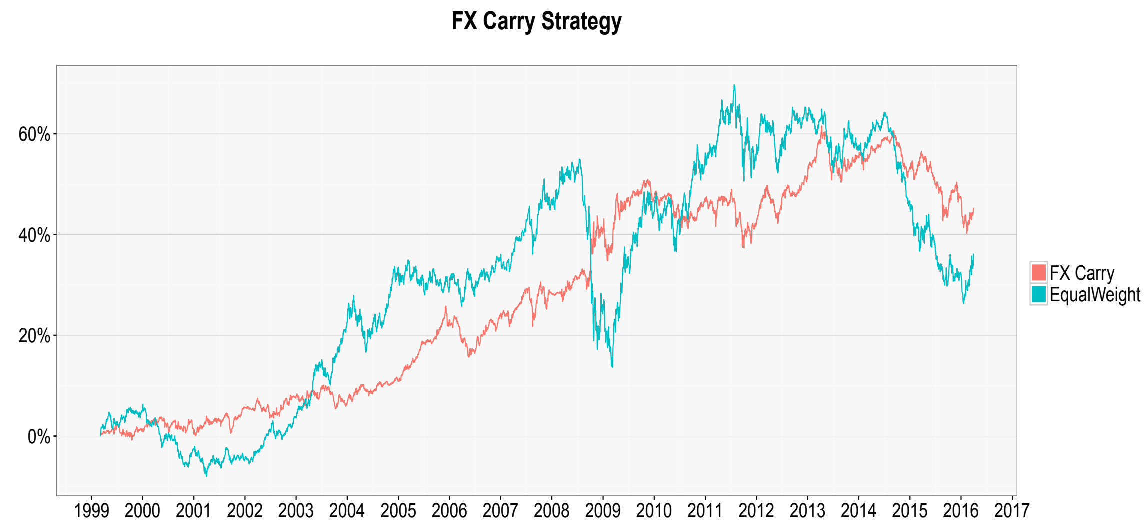

FIGURE 5.7: FX Carry Strategy - Performance

	FX Carry	EqualWeight
Cumulative Return	0.45	0.36
Annualized Return	0.02	0.02
Annualized Standard Deviation	0.05	0.08
Annualized Sharpe Ratio (rf=0%)	0.44	0.23
Worst Drawdown	0.13	0.27
Average Drawdown	0.01	0.02
Skewness	-0.18	-0.32
Kurtosis	11.73	7.46

TABLE 5.6: FX Carry Strategy - Performance Statistics

The above table reveals a Sharpe ratio that is almost double that of its benchmark. Realizing an above 0.40 Sharpe ratio for a strategy trading solely in an asset class that confers no holding benefit, should be sufficient proof of the existence of this alternative risk premium. On a more contemporaneous note, one should note that currency carry strategies have performed poorly in the last five years. The main explanation behind these recent performances is attributed to the expansionary monetary policies that most developed market central banks implemented following the global financial crisis. Even in light of this, we remain confident in the attractiveness of this risk premium, especially from a forward looking perspective.

5.5.2 Commodities

The commodity carry strategy's cumulative returns are presented below. This is our highest Sharpe ratio strategy, realizing 1.92 over the backtest period. Such a high ratio is explained by the extreme amount of leverage required by the strategy (400%). Even with such leverage, the strategy barely generates 2.00% annualized returns. Investors are often leverage constrained and shun risk premia that require a lot of it. It stands to reason that the participants willing or able to underwrite those risks do so at attractive premia levels. In this particular case, this effect is compounded by the fact that retail investors have a limited access to the commodity markets because of different financial regulations aimed at protecting them. This further limits the amount of capital being deployed toward this risk premium. When compared to its benchmark, the commodity strategy offers an extremely stable return profile that exhibits none of the cyclicality inherent to this asset class' returns. Commodities are highly volatile yet, when harvesting carry risk premium, the resulting volatility is reduced seventeen fold relative to that of a long-only portfolio of these assets. The maximum drawdown statistics are also impressive; the strategy suffering a maximal loss of a mere 2%. This seems almost insignificant when compared to the benchmark's 57% loss in 2008.

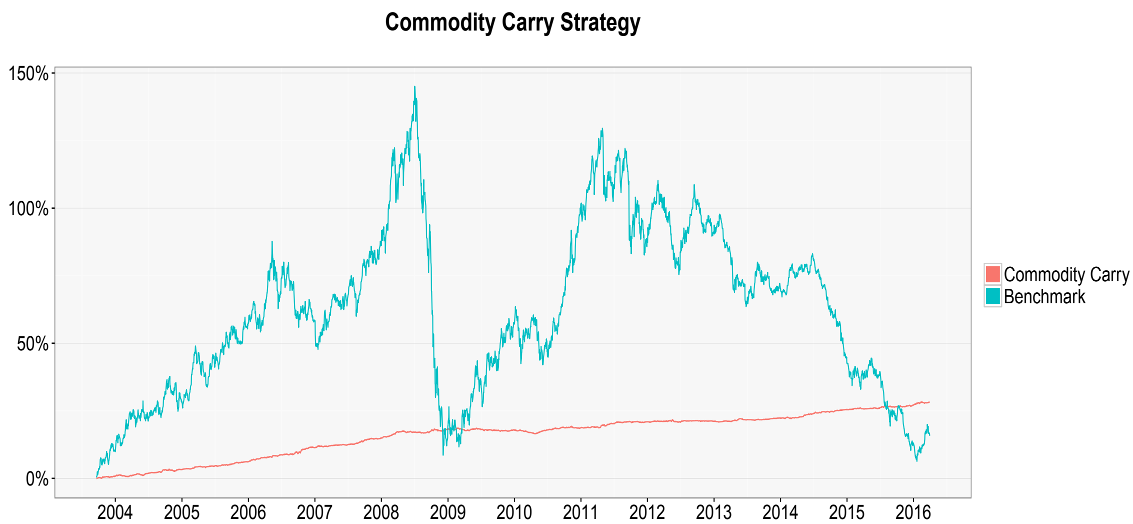

FIGURE 5.8: Commodity Carry Strategy - Performance

	Commodity Carry	Benchmark
Cumulative Return	0.28	0.16
Annualized Return	0.02	0.01
Annualized Standard Deviation	0.01	0.17
Annualized Sharpe Ratio (rf=0%)	1.92	0.07
Worst Drawdown	0.02	0.57
Average Drawdown	0.00	0.03
Skewness	0.50	-0.31
Kurtosis	7.06	6.97

TABLE 5.7: Commodity Carry Strategy - Performance Statistics

Chapter 6

Momentum Strategy

6.1 Literature Review

Long shun by the academic community, the momentum risk premia were long harvested by the industry's practitioners. This was notably the case for equity traders and portfolio managers as described in Grinblatt's work [46]. The initial momentum strategies were initially studied as a characteristic of single stock equity instruments. Jegadeesh [47] and Asness [48], are two authors that were famous for their analyses of the subject.

As momentum investing gained acceptance in the academic research community, its associated risk premia were identified as an important characteristic of most financial assets. Commodities, fixed income instruments, and currencies all exhibit a momentum risk premium that is pervasive in time. One of the longest empirical study of momentum is credited to Hurst in 2014 [49]. In it, the author extended Moskowitz's [50] time series momentum strategy over a century of data. His findings, validating the existence of the risk premia, were corroborated in an unrelated paper published by Lemperiere [51].

There exists two types of momentum risk premia; the cross sectional momentum, and the time series momentum. The strategy, developed as part of this research, belongs to the latter category. Unlike cross-sectional momentum, which are often dollar or beta neutral, time series momentum strategies typically implement long, neutral, or short tactical positions within a diversified universe of financial assets with no such constraints.

6.2 Investment Universe

Below is a list of the instruments that are transacted as part of the strategy. The most liquid futures contracts from all asset classes are used.

Ticker	Bloomberg Code	Description	Asset Class
ES1	ES1 Index	E-mini S&P 500 Future	Equity
NK1	NK1 Index	Nikkei 225 Index Future	Equity
VG1	VG1 Index	Euro STOXX 50 Index Future	Equity
PT1	PT1 Index	S&P Toronto 60 Future	Equity
XP1	XP1 Index	ASX SPI 200 Future	Equity
TY1	TY1 Comdty	US Treasury 10-Year Future	Fixed Income
RX1	RX1 Comdty	German Government Euro Bund Future	Fixed Income
JB1	JB1 Comdty	Japanese Government Bond 10-Year Future	Fixed Income
US1	US1 Comdty	US Treasury Long Bond Future	Fixed Income
CN1	CN1 Comdty	Canadian Governement Bond 10-Year Future	Fixed Income
FV1	FV1 Comdty	US Treasury 5-Year Note Future	Fixed Income
CL1	CL1 Comdty	Crude Oil Future	Commodity
GC1	GC1 Comdty	Gold Future	Commodity
HG1	HG1 Comdty	Copper Future	Commodity
NG1	NG1 Comdty	Natural Gas Future	Commodity
LC1	LC1 Comdty	Live Cattle Future	Commodity
S_1	S 1 Comdty	Soybean Future	Commodity
W_1	W 1 Comdty	Wheat Future	Commodity
C_1	C 1 Comdty	Corn Future	Commodity
SB1	SB1 Comdty	Sugar Future	Commodity
LH1	LH1 Comdty	Lean Hog Future	Commodity
FC1	FC1 Comdty	Feeder Cattle Future	Commodity
QS1	QS1 Comdty	Gas Oil Future	Commodity
CC1	CC1 Comdty	Cocoa Future	Commodity
CO1	CO1 Comdty	Brent Oil Future	Commodity
SI1	SI1 Comdty	Silver Future	Commodity
AD1	AD1 Curncy	AUD/USD Future	FX
JY1	JY1 Curncy	JPY/USD Future	FX
BP1	BP1 Curncy	GBP/USD Future	FX
EC1	EC1 Curncy	EUR/USD Future	FX
CD1	CD1 Curncy	CAD/USD Future	FX
NV1	NV1 Curncy	NZD/USD Future	FX
PE1	PE1 Curncy	MXN/USD Future	FX

TABLE 6.1: Momentum - Investment Universe

6.3 Signals & Order Sizing

6.3.1 Momentum Signals

There are many ways to estimate the momentum risk premium. The most popular approach was proposed in Moskowitz's seminal paper [50] on the subject. In it, he finds that the momentum effect is statistically significant when measured across 1 to 12 months windows. We were mindful of these findings when developing our momentum strategy. However, instead of selecting a single window by which we estimate an instrument's price momentum, we selected three: 3-months, 6-months, and 12-months. Timeframes below 3-months were not considered as those estimation windows tend to be dominated by mean reverting dynamics rather than momentum. For the three timeframes, we compute their 13, 26, and 52 weekly rolling moving averages using weekly closing prices as defined below:

$$A_w = \sum_{i=1}^{n} \frac{P_{(w-i)+1}}{n} \tag{6.1}$$

where

w is the moving average's week
n is the moving average's period
P is the weekly close price of the data series

For a given futures, the above indicators' values are then converted into three separate trading signals by comparing its weekly closing price to each indicators value. A price that exceeds the indicator value results in a long signal, whereas a price below the indicator value results in a short signal. The below equation specifies the signal construction:

$$Signal = \begin{cases} +1, \text{if } P_w - A_w \geq 0 \\ -1, \text{otherwise} \end{cases}$$

where

$+\,1$ corresponds to a go long signal
$-\,1$ corresponds to a go short signal

From the signals, we create momentum sub-strategies that are applied to each instrument. As an example, for each equity futures trade as part of the strategy, we create three momentum sub-strategies. To ensure no look ahead bias is introduced in these sub-strategies, we apply the trading signals with one day of slippage. However, we do not account for any transactions costs yet. The three figures below illustrate these return series for the equity futures contracts. The same is done for all the other instruments as well.

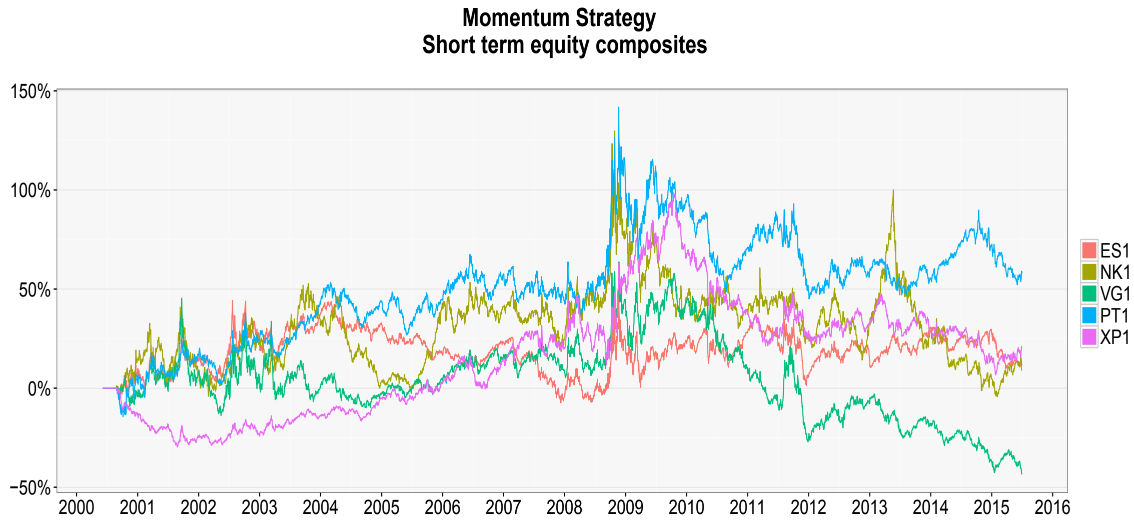

FIGURE 6.1: Short Term Momentum - Equity Composites

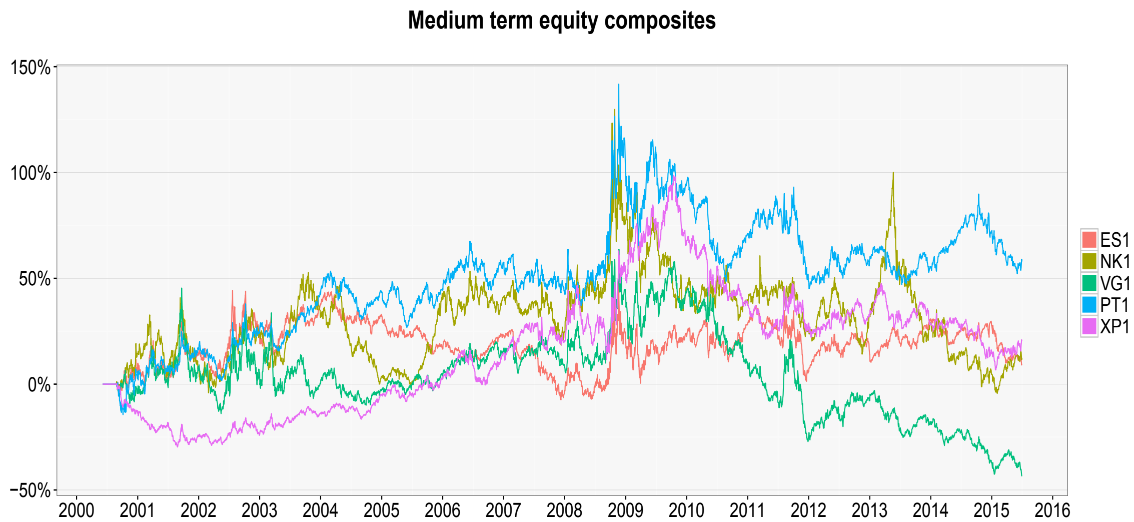

FIGURE 6.2: Medium Term Momentum - Equity Composites

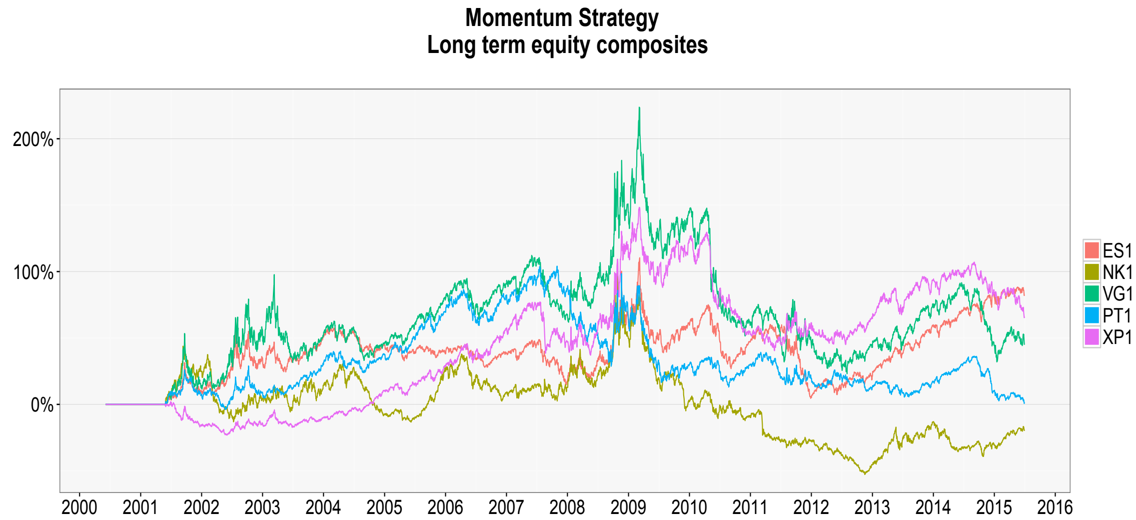

FIGURE 6.3: Long Term Momentum - Equity Composites

6.3.2 Order Sizes

The strategy's order sizes are obtained from the composites computed above. The methodology contains many steps and bears careful explanation. First, for the composites of a given asset class, we perform an ERC optimization by momentum timeframe (ST, MT, LT). Continuing our example with the equity contracts, we would optimize three portfolios: one composed of short term equity momentum sub-strategies, another of medium term sub-strategies, and a last one of longer term sub-strategies. The ERC optimization problem is detailed in Chapter 3. We use the same resolution method for this as the one used to obtain the risk parity portfolio.

For each time-frame, the optimizations are specified to allow for over-investment or under-investment at the portfolio level, as well as at the composite levels. We also do not allow negative allocations (shorts) to a specific composite. Finally, the covariance matrices are estimated using the last 90 days realized returns, and the portfolio weights are updated on a monthly basis. The code-block below provides some insight in the specifications we just outlined.

```
# Short Term Equity ERC
Weights.ERC(returns = equity.model$st$instruments$returns,
            rebalancing.frequency = "months",
            optimization.type = "risk_budget",
            objective.function = "StdDev",
            w.min = 0.00,
            w.max = 1.50,
            w.sum.min = 0.50,
            w.sum.max = 1.25,
            training.period = 90,
            trailing.period = 90)
```

LISTING 6.1: Momentum - Equity ST Momentum ERC Code

Within each asset class, a total of three optimizations (like the one above) are performed. This results in allocation weights for each three momentum (short term, medium term, long term) sub-strategies. These weights are once again lagged by a full day (to account for slippage), and used in creating three composites (short term, medium term, long term) per asset classes. These three composites are then used in another ERC optimization with the same specifications. The result of this optimization is the final asset class composite whose weights are an optimal blend of short term, medium term, and longer term momentum risk premia for each instrument. Staying with our equity contracts, we present these intermediary results below:

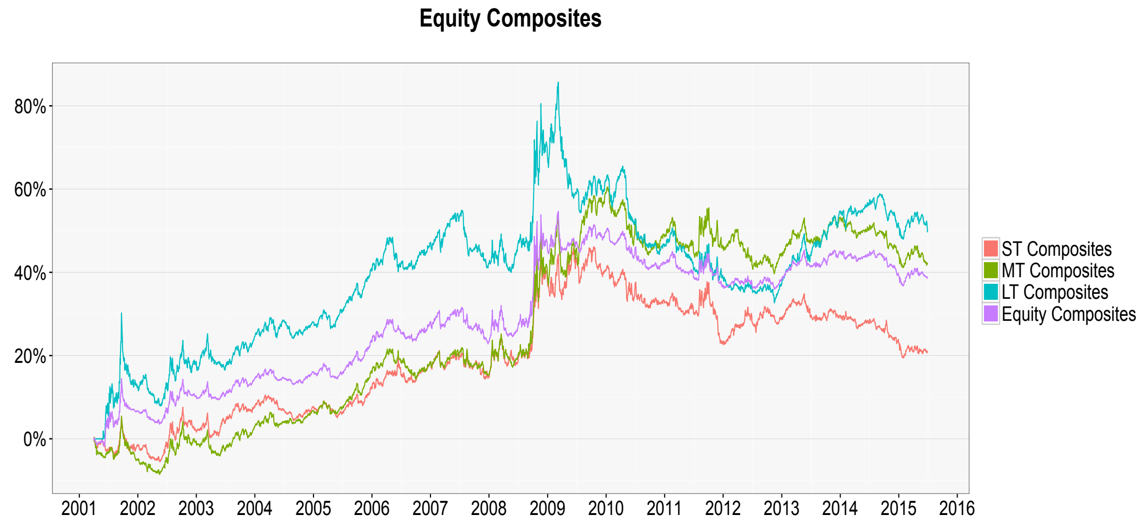

FIGURE 6.4: Momentum Strategy - Equity Composites

For each asset class, the four weights matrices, associated to each of the composites (as the ones presented above), are used to backtrack the optimal instrument weights. The code block below illustrates this final step. First, the final asset classes composites are recreated from these weights matrices, and are then used as inputs in a final ERC optimization that determines the optimal asset class exposures of the strategy. The result of this optimization is then used to obtain the final strategy weights by backtracking each instrument's weights.

```
# Update Equity Weights
returns_equity        <- Return.calculate(futures_equity[" first .day::day"]
portfolio_equity      <- Return.portfolio(returns_equity, lag(weights_equity, k = 1))

# Update Fixed Income Weights
returns_fixedincome      <- Return.calculate(futures_fixedincome["first.day::day"]
portfolio_fixedincome    <- Return.portfolio(returns_fixedincome, lag(weights_fixedincome, k = 1))

# Update Commodities Weights
returns_commodities      <- Return.calculate(futures_commodities["first.day::day"]
portfolio_commodities    <- Return.portfolio(returns_commodities, lag(weights_commodities, k = 1))

# Update Commodities Weights
returns_commodities      <- Return.calculate(futures_commodities["first.day::day"]
portfolio_commodities    <- Return.portfolio(returns_commodities, lag(weights_commodities, k = 1))

# Update Asset Class Weights
returns_assetclass      <- bind(portfolio_equity, portfolio_fixedincome, portfolio_commodities)
weights_assetclass     <- Weights.ERC(returns = returns_assetclass,
                          rebalancing.frequency = "months",
                          optimization.type = "risk_budget",
                          objective . function = "StdDev",
                          w.min = 0.00,
                          w.max = 1.50,
                          w.sum.min = 0.50,
                          w.sum.max = 1.25,
                          training . period = 90,
                          trailing . period = 90)

# Backtrack the individual futures weights
weights_portfolio  <- bind(weights_assetclass[, "equity"] * weights_equity, weights_assetclass[, "
    fixedincome"] * weights_fixedincome, weights_assetclass[,"commodities"] * weights_commodities
returns_portfolio     <- Return.portfolio(returns_futures, weights_portfolio)
```

LISTING 6.2: Momentum Strategy - Across Assets Weights

6.4 Strategy Implementation

Using the strategy weights, we backtested the portfolio under daily, weekly, monthly and quarterly rebalancing. At the risk of repeating ourselves, each backtest were implemented using a full day of slippage between trades, and transaction costs of 1 basis point. This strategy is a good example of the impact that transactions cost can have. Apart from the yearly rebalanced strategy, which doesn't efficiently implement the trading signals, the daily rebalanced strategy is the worst. One would expect that time-series momentum signals are better implemented as soon as they are triggered, but as shown below, the impact of transactions costs can rapidly mitigate this advantage.

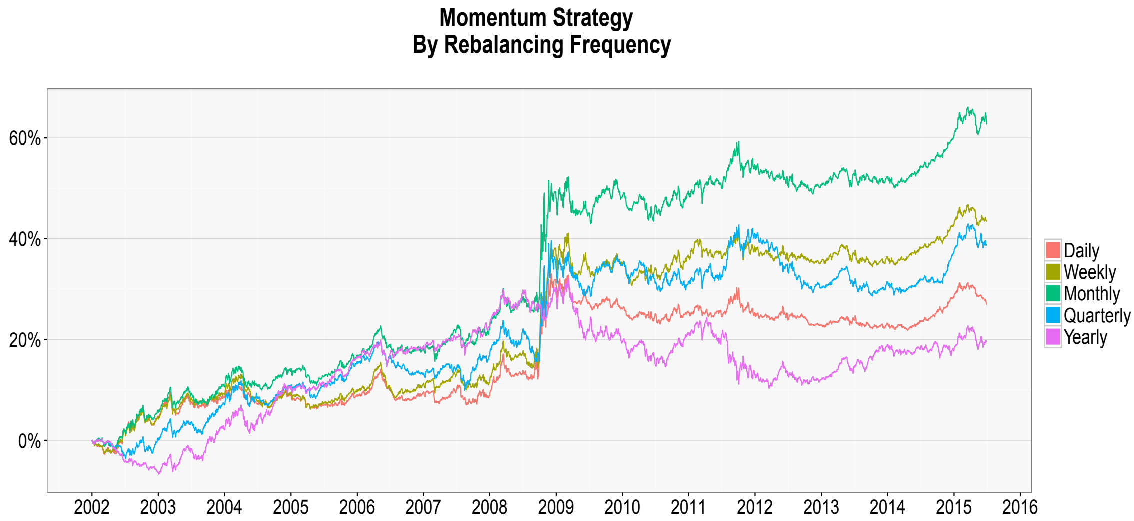

FIGURE 6.5: Momentum Strategy - Trading Frequency

	Daily	Weekly	Monthly	Quarterly	Yearly
Cumulative Return	0.27	0.43	0.63	0.39	0.20
Annualized Return	0.02	0.03	0.04	0.02	0.01
Annualized Standard Deviation	0.04	0.05	0.05	0.05	0.04
Annualized Sharpe Ratio (rf=0%)	0.41	0.56	0.71	0.46	0.30
Worst Drawdown	0.08	0.07	0.08	0.10	0.16
Average Drawdown	0.02	0.01	0.01	0.01	0.01
Skewness	0.80	0.83	0.95	0.92	-0.24
Kurtosis	23.30	19.74	28.38	28.44	5.64

TABLE 6.2: Momentum Strategy - Trading Frequency

The monthly rebalanced strategy is the obvious implementation choice. Its Sharpe ratio stands highest at 0.71, and its total return far outpaces the other implementations. However, as all our other strategies were implemented on weekly basis, we opted to do so here as well. We end up sacrificing a bit of Sharpe ratio with this choice. This being said, we are confident that a weekly rebalancing policy strikes an appropriate balance between trading reactivity and overall costs.

As this strategy is one of our most active in terms of trading, we present the impacts that different transaction costs have on its returns characteristics. At 5 basis points, the strategy's performance statistics really start deteriorating. An investor bearing trading costs that are above 20 basis points would not capture this risk premium. He would instead suffer negative returns trading our strategy.

	0.00%	0.05%	0.10%	0.15%	0.20%	0.25%
Cumulative Return	0.43	0.28	0.15	0.02	-0.08	-0.18
Annualized Return	0.03	0.02	0.01	0.00	-0.01	-0.01
Annualized Standard Deviation	0.05	0.05	0.05	0.05	0.05	0.05
Annualized Sharpe Ratio (rf=0%)	0.55	0.38	0.21	0.04	-0.13	-0.30
Worst Drawdown	0.07	0.08	0.12	0.16	0.20	0.23
Average Drawdown	0.01	0.02	0.03	0.04	0.04	0.08
Skewness	0.82	0.83	0.84	0.84	0.85	0.85
Kurtosis	19.68	19.66	19.60	19.49	19.35	19.17

TABLE 6.3: Momentum Strategy - Trading Costs

6.5 Performance Metrics

The below figure and table present the selected strategy's performance relative to a long-only benchmark composed of the same instruments. As for the risk premia and value strategies, the benchmark was constructed by equal weighting each instrument within an asset class, and then allocating equally to the asset classes composites. This ensures that we compare the strategy to a well balanced benchmark. An important characteristic inherent to the momentum risk premium is exhibited below. Contrary to most investment portfolios, momentum strategies tend to have a "long-volatility" bias. Such strategies perform particularly well in turbulent / crises market environment, followed by a period of lackluster performance[1]. We see this exact behaviour when looking at the strategy's return between 2008 and 2009.

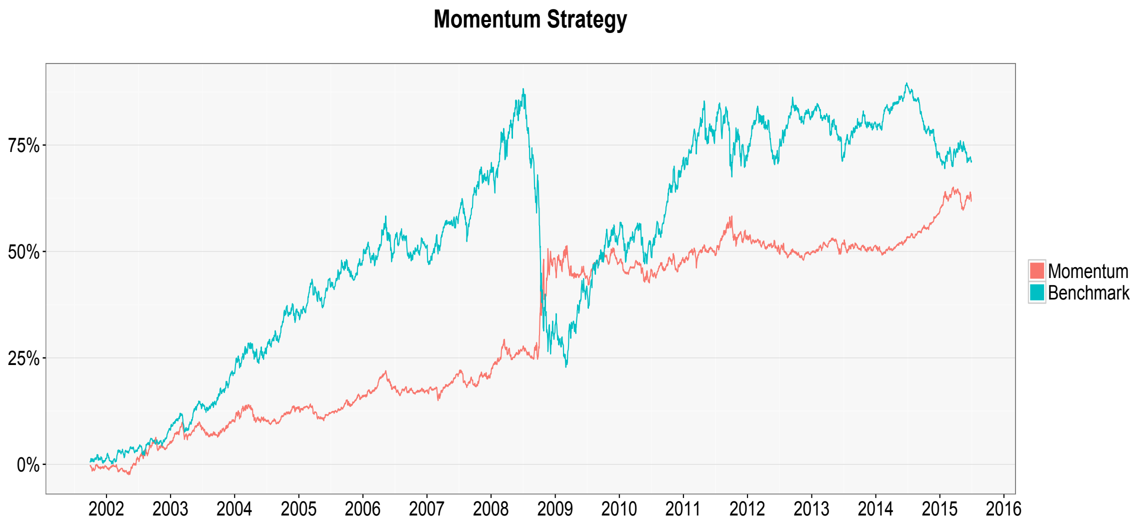

FIGURE 6.6: Momentum Strategy - Performance

[1]This characteristic is known as "Momentum Crashes".

	Momentum	Benchmark
Cumulative Return	0.40	0.66
Annualized Return	0.02	0.04
Annualized Standard Deviation	0.05	0.08
Annualized Sharpe Ratio (rf=0%)	0.52	0.46
Worst Drawdown	0.07	0.35
Average Drawdown	0.01	0.02
Skewness	0.82	-0.62
Kurtosis	19.68	9.64

TABLE 6.4: Momentum Strategy - Performance Statistics

Chapter 7

Portfolio Construction

7.1 Literature Review

Following Markowitz's modern portfolio theory (MPT) [6], there has been an explosion of academic papers tackling to the portfolio selection problem. Sharpe (1964) Treynor (1962), Litner (1965) and Mossin (1966) all built upon Markowtiz's ideas to propose the Capital Asset Pricing Model (CAPM). For the first time, academic researchers and market practitioners alike were now armed with a formal framework by which to tackle asset allocation problems. As often the case in finance, the first focus of these researchers were geared toward equity centric portfolios, which in turn led to the development of the market capitalization weighted indices, and of the mutual fund industry.

Years after the CAPM's discovery, others sought to expand the model. The Arbitrage Pricing Theory (APT), proposed by Ross [52], and later the Fama and French multi factor models [18] were attempts at such. These expanded models led to improvements in portfolio construction methodologies that took factor tilting, and hedging into consideration. By the mid 1990's the hedge fund industry gained prominence, and these new asset allocation methodologies were quickly adopted by their market practitioners. In a departure from the classic 60/40 equity bonds allocations, it was trading strategies like the constant proportional portfolio insurance (CPPI) [53] that saw widespread adoption.

Through the emergence of computers and quantitative risk management techniques, practitioners and academic alike started identifying limits to the traditional mean variance portfolio framework. This led them to embark on the development of portfolio construction methodologies that addressed the problems inherent to mean-variance optimized portfolios. Chief among these were the issues surrounding the proper estimation of financial assets expected returns, a key component of the mean-variance model. Alongside these problems were also the excessive asset concentration that these portfolios sometimes exhibited. All these issues, and more, were described by Goldman Sachs, Fisher Black and Robert Litterman's in a seminal paper [54]. In it, they propose a portfolio construction methodology that alleviates these two problems; the Black-Litterman Model. Around the same period, a handful of other asset allocation models would become popular amongst market practitioners. Equal weighted portfolios (long overlooked by academic researchers), Minimum Variance portfolios, Equally risk weighted portfolios [12], and Maximum Diversification portfolios [55] all became widely adopted by market practitioners following the large losses borne by traditional mean-variance and 60/40 portfolios during the global financial crisis. These methodologies all have a common point in that they focus, on redefining "risk" in a way that their resulting portfolios are robust out of sample. Today, smart beta and risk parity portfolios owe their popularity to these methods.

Although vast and rich, the portfolio construction literature seldom sought to apply these methods to alternative risk premia portfolio. We know the characteristics of their portfolios when composed of long-only financial assets, but when it comes to portfolios of alternative, we have few empirical evidences of their usefulness. A goal of this research, is to revisit these portfolio construction methodologies and use them in allocating across the alternative risk premia strategies developed in the prior sections. We chose to limit ourselves to "robust" portfolio construction methodologies. By that, we mean that we consider only approaches that do not require the estimation of expected returns. This is coherent with the current market orthodoxy. Indeed, as stated by Roncalli: "Looking at the marketplace, it also appears that a large fraction of investors prefers more heuristic solutions, which are computationally simple to implement and are presumed robust as they do not depend on expected returns." [12].

7.2 Strategies

7.2.1 Strategy Universe

The table lists the strategies used to construct as part of our risk premia portfolio. As some strategies have longer performance histories[1], we normalized their inception date and end date to be the same.

Strategy	Inception	End	Ann. Return (%)	Ann. Volatility (%)
Risk Parity	2007-01-01	2015-06-30	3.29	3.62
Momentum	2007-01-01	2015-06-30	2.28	4.51
Value	2007-01-01	2015-06-30	2.77	4.94
Commodity Carry	2007-01-01	2015-06-30	1.43	0.9
FX Carry	2007-01-01	2015-06-30	4.02	7.06

TABLE 7.1: Portfolio Construction - Investment Universe

7.3 Portfolios

We construct four alternative risk premia portfolio. Each portfolio, is rebalanced on weekly basis so as to match the rebalancing frequencies of its underlying strategies. Since we work with the strategies data directly, and that their returns are already net of trading fees (as per the backtests presented herein), we adjust our portfolio rebalancing costs to 0.50 basis points and a full day of slippage. This mitigates the effects associated to double counting transaction costs. It remains however overly conservative as the strategies long-short exposures net themselves when combined in a portfolio. This gives rise to less trading than we simulated in our own portfolio backtests. We are cognizant of this, but retain this stance as we prefer to err on the side of caution and overestimate the portfolio's transactions costs rather than underestimate them. An alternative to adjusting the trading costs downward would be to implement a more granular backtest that uses and adjusts the strategy's underlying weights directly. We will integrate this approach in future works.

[1] The backtests were conducted based on the longest instruments data availability.

For each portfolio construction approach tested, we enforced the strategies weights to sum to 100% and constrained them to be positive (meaning we can't short a strategy). The diversification benefits that arise from combining the different strategies together mean that the resulting portfolio's volatility is significantly reduced. However, an advantage of risk premia investing through futures is that one can access leverage. As such, an investor can dynamically lever its portfolio so that it realizes a desired volatility level. We apply such a leverage adjustment to our portfolios. The below section details our exact leverage methodology.

7.3.1 Leverage Adjustments

As most of our strategies exhibit volatilities below 5.00%, the resulting portfolios also realize a volatility well below this level. To address this, we leverage the portfolio to a 5.00% annualized volatility target while limiting its gross leverage factor up to 500% (5X leverage). As certain strategies already have a certain amount of leverage embedded in them, some portfolios might at certain points in time have gross exposures in excess of 500%. The leverage adjustment factors are computed from the average of two measures. The first is based on the portfolio's 90 days realized volatility. The second is based on the portfolio's forward looking volatility as derived from a GARCH model.

The first measure is derived below. First, we compute the portfolio's 90 days realized volatility. Then annualize it. And finally convert the estimate into a leverage factor based on the desired volatility target. These computation steps are outlined below:

$$\sigma_{t,t-90} = \sqrt{\frac{1}{N}\sum_{t-90}^{t}(x_t - \overline{x})^2} \tag{7.1}$$

$$\sigma_{Realized,t} = \sigma_{t,t-90}\sqrt{252} \tag{7.2}$$

$$Leverage_{Realized,t} = \frac{\sigma_{Target}}{\sigma_{Realized,t}} \tag{7.3}$$

where

x_t are the daily returns of the portfolio

$\sigma_{Realized,t}$ is the annualized realized volatility over the last 90 days

$Leverage_{Realized,t}$ is the leverage target derived from the portfolio's realized volatility

The second leverage measure is derived from the portfolio's forward looking volatility estimate. We obtain this estimate by positing that the portfolio's volatility follows a GARCH process. We do not make any explicit assumptions relative to the specific type of GARCH process it follows. Instead, we cycle through multiple models until we obtain the best fit. This is achieved using the model fitting functions found in R's RUGARCH package. The exact details surrounding the model selection and fit procedures employed in this package are beyond the scope of this research[2]. The code block

[2] Should the detail conscious reader seek more information, we refer him to the package's documentation [56] and direct him to the following functions (ugarchspec, ugarchfit).

below provides some insight in our volatility estimating procedure. We fit the GARCH models every week using the portfolio's last 300 days of returns. At each step, we test the model fit and model forecasts for convergence. In the instances when the model does not converge, we re-specify it and refit it while expanding the sample period by a day at a time. We do this until the model converges. The forward leverage target is computed from the 5 days ahead forecast of the portfolio's volatility. The full R code of the function used to compute this leverage measure is presented here after:

```r

# Function definition
Leverage.factor <- function(returns, vol.target, max.gross) {

# Compute the realized leverage factor
vol.realized <- na.omit(apply.rolling(R = returns, width = 90, by = 1, FUN = "StdDev.annualized"))
vol.leverage <- vol.target / vol.realized
realized.leverage <- na.omit(vol.leverage)
realized.leverage[realized.leverage > max.gross] <- max.gross

# Compute the forward looking leverage factor
garch.leverage <- returns * NA
   for(i in seq(from = 300, to = nrow(returns), by = 5)) {

   # Specify an open garch model
   garch.spec <- ugarchspec()
   garch.fit     <- try(ugarchfit(spec = garch.spec, data = returns[((i-299):i), ]), silent = TRUE)
   garch.conv <- try(convergence(object = garch.fit), silent = TRUE)

    # If the garch fit doesn't converge, prune the sample returns until it does
    j <- i
    while(garch.conv != 0 | is(garch.fit, "try-error")){
       j          <- (j - 1)
      garch.fit <- try(ugarchfit(spec = garch.spec, data = returns[((j-299):j), ]), silent = TRUE)
      garch.conv <- try(convergence(object = garch.fit), silent = TRUE) }

   # Forecast the week ahead volatility
   garch.forecast <- try(ugarchforecast(garch.fit, n.ahead = 5), silent = TRUE)

  # If the garch forecast doesn't converge, prune the sample returns until it does
  j <- i
  while( is(garch.forecast, "try-error") ) {
      j <- j - 1
      garch.fit       <- try(ugarchfit(spec = garch.spec, data = returns[((j-299):j), ]), silent =
     TRUE)
      garch.forecast <- try(ugarchforecast(garch.fit, n.ahead = 5), silent = TRUE) }

# GARCH leverage
garch.leverage [i] <- last(sigma(garch.forecast)) * sqrt(252) }

# Bound the GARCH leverage factor
garch.leverage[garch.leverage > max.gross] <- max.gross
garch.leverage <- na.locf(garch.leverage)

# Final Leverage Factor
leverage.factor <- na.omit(realized.leverage + garch.leverage) / 2
return(leverage.factor) }
```

LISTING 7.1: Forward Leverage Measure Code

To account for the trading costs associated to this added layer of complexity, we apply the leverage factors on a weekly basis at the same time we are rebalancing the portfolios. As always, a day of slippage, and 0.50 basis point trading costs are included in our backtests. It is important to note that the resulting portfolios do not exactly reach their volatility targets. Indeed, in the presence of trading costs, the increased trading, required to manage the portfolio leverage, can quickly become detrimental to its performance. The below figure demonstrates this phenomenon on the risk parity strategy. Without trading costs, if the strategy is rebalanced on a daily basis to its leverage factor, it just slightly overshoots its volatility target. However, in the presence of trading costs (willingly exaggerated to 1 basis points) the strategy's volatility increases, but is nowhere near its target. Furthermore, all this excessive trading reduces its returns, further impacting its Sharpe ratio negatively. The same happens at the portfolio level.

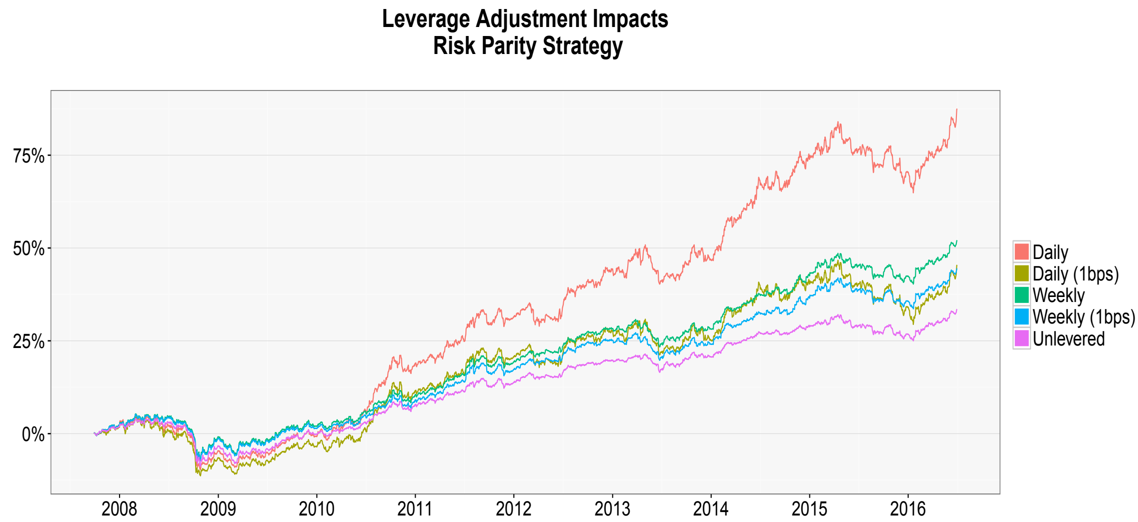

FIGURE 7.1: Leverage Adjustments - Trading Costs

	Daily	Daily (1bps)	Weekly	Weekly (1bps)	Unlevered
Cumulative Return	0.88	0.45	0.52	0.45	0.34
Annualized Return	0.07	0.04	0.05	0.04	0.03
Annualized Standard Deviation	0.06	0.06	0.04	0.04	0.04
Annualized Sharpe Ratio (rf=0%)	1.15	0.67	1.11	0.97	0.88
Worst Drawdown	0.14	0.15	0.12	0.12	0.12
Average Drawdown	0.01	0.01	0.01	0.01	0.01
Skewness	-0.29	-0.31	-0.14	-0.19	-0.85
Kurtosis	5.09	5.11	8.40	8.41	13.66

TABLE 7.2: Leverage Adjustments - Performance

7.3.2 Equal Weight

Often overlooked by academic researchers, equal weighted portfolios are very popular among market practitioners. Empirical evidence of their popularity can notably be found in Bernartzi and Thaler's work [**Bernatzi2001**]. At face value, they may seem overly simple, but this allocation methodology possesses surprising empirical properties. The most important of them is its out of sample robustness, especially relative to mean-variance efficient portfolios. Indeed, the theoretical performance of mean-variance efficient portfolio often translates to poor empirical out of sample performance [57]. Furthermore, equally weighted portfolios are often more resilient to drawdowns than their mean-variance based counterparts. The latter are often too concentrated, and suffer accordingly during market crashes. These appealing characteristics justify testing their performance when constructing risk premia portfolios.

An equally weighted portfolio's allocations can be represented as:

$$w_i = \frac{1}{N} \tag{7.4}$$

where

w_i is the proportion of the portfolio capital allocated to the asset i

N is the total number of assets in the portfolio's investment universe

Applying this allocation methodology to a portfolio composed of our risk premia strategies, we obtain a portfolio that generates a Sharpe ratio above 1.00. These results assume weekly rebalancings of the net of fees strategies with an added 0.50 basis point of trading costs. One day of slippage is also applied. The figure below presents the cumulative returns associated to this portfolio construction approach. The table reveals what we alluded to earlier, the levered portfolio, although more volatile, doesn't reach our desired volatility target.

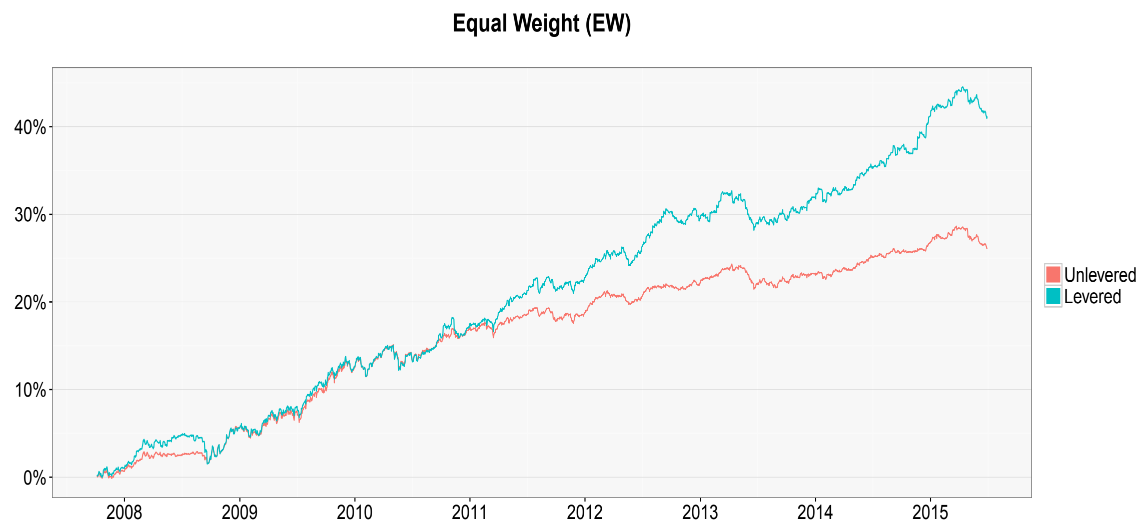

FIGURE 7.2: Equal Weight Portfolio - Performance

	Unlevered	Levered
Cumulative Return	0.26	0.41
Annualized Return	0.03	0.04
Annualized Standard Deviation	0.02	0.03
Annualized Sharpe Ratio (rf=0%)	1.27	1.47
Worst Drawdown	0.02	0.03
Average Drawdown	0.00	0.00
Skewness	-0.14	-0.18
Kurtosis	6.60	7.96

TABLE 7.3: Equal Weight Portfolio - Performance Metrics

7.3.3 Minimum Variance

Minimum variance portfolios have recently seen a renewed interest by market practitioners. This approach was initially viewed as a solution to overcome the issues surrounding the mean-variance framework. Clarke, and al. [58] studied the characteristics of this portfolio construction methodology by applying it US Equity instruments. He found that, although one is not required to estimate the portfolio's assets expected returns, proper care must still be applied when constructing minimum variance portfolios, especially in cases when the number of assets (N) in the portfolio is large. This is not the case for our portfolio (N = 5).

We specify our Minimum Variance Portfolio as a constrained optimization problem:

$$\begin{aligned} \underset{w}{\text{minimize}} \quad & \sigma_p = w'\Omega w \\ \text{subject to} \quad & sumw_i = 1,\ i = 1, \ldots, N. \\ & w_i \geq 0. \end{aligned}$$

where

w is the optimal set of weights
Ω is the estimated covariance matrix of strategy returns
N is the total number of strategies in the portfolio

When unconstrained, minimum variance portfolios often lead to large turnover. This was reported to be the case of equity portfolios, monthly turnover statistics hover around 11.9% [58], a significant amount of rebalancing by any standard. More importantly, is the fact that these portfolios are, similarly to mean-variance portfolios, often highly concentrated in a few assets. To address this, we build two portfolios of strategies. The first is unconstrained, except for the 100% leverage and weights positivity constraints that are outline in the above equation. The second portfolio is constrained so that its strategies weights are within the following range:

Strategy	Minimum Weight	Maximum Weight
Risk Parity	30%	65%
Momentum	10%	40%
Value	10%	40%
Commodity Carry	10%	40%
Currency Carry	10%	40%

We solve for the portfolio weights with a quadratic solver. R's ROI, is such a solver and can be found as part of the Portfolio Analytics's library. The covariance matrix are estimated using a rolling 90 days returns window, and the weights are rebalanced on weekly basis. For both portfolio, we present their levered and unlevered cumulative returns and performance statistics. We discuss their results in the analysis section.

Unconstrained

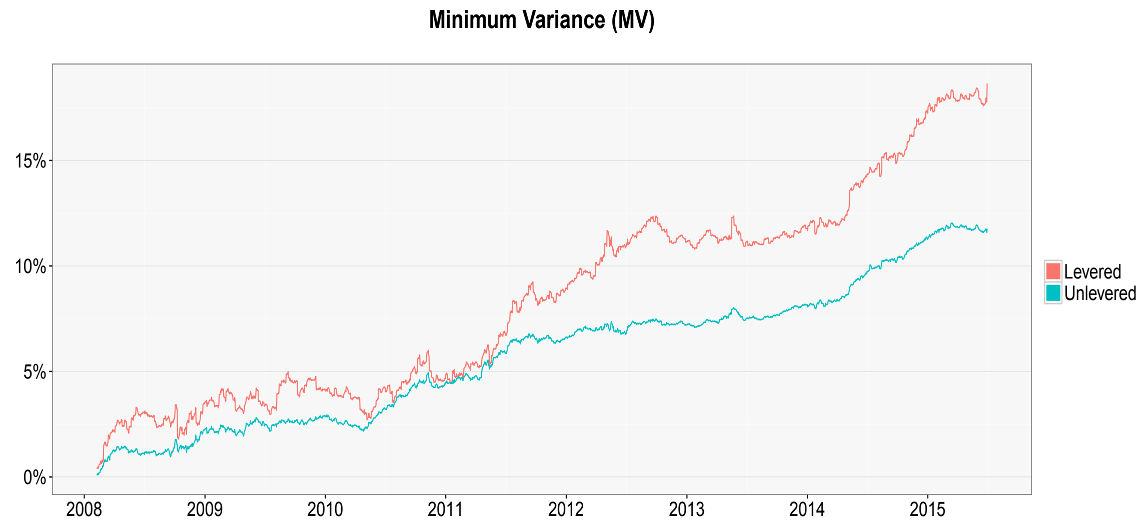

FIGURE 7.3: Unconstrained MV Portfolio - Performance

	Levered	Unlevered
Cumulative Return	0.19	0.12
Annualized Return	0.02	0.01
Annualized Standard Deviation	0.02	0.01
Annualized Sharpe Ratio (rf=0%)	1.21	1.75
Worst Drawdown	0.02	0.01
Average Drawdown	0.00	0.00
Skewness	-0.14	0.01
Kurtosis	20.35	5.01

TABLE 7.4: Unconstrained MV Portfolio - Performance Metrics

Constrained

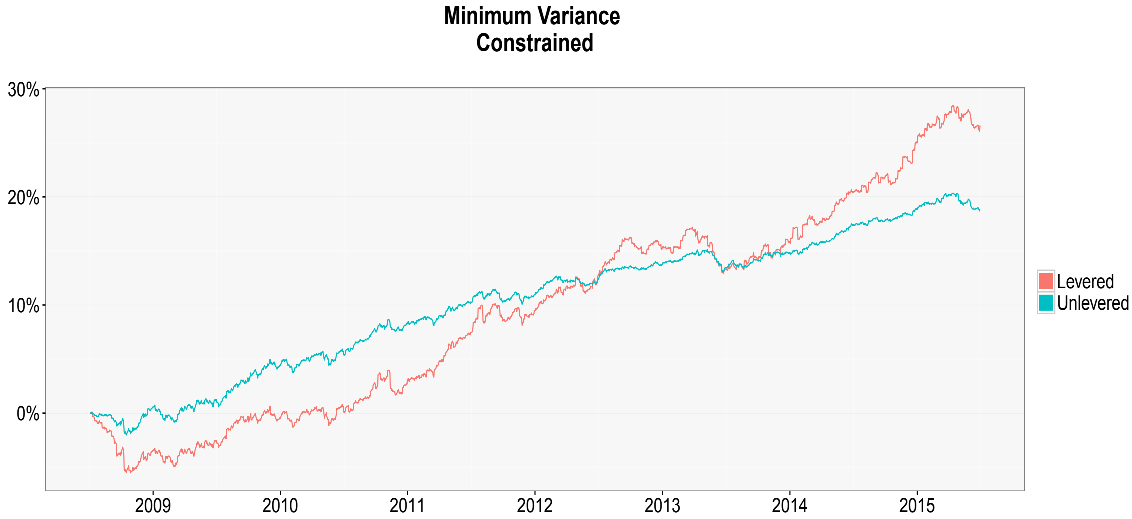

FIGURE 7.4: Constrained MV Portfolio - Performance

	Levered	Unlevered
Cumulative Return	0.27	0.19
Annualized Return	0.03	0.02
Annualized Standard Deviation	0.03	0.02
Annualized Sharpe Ratio (rf=0%)	1.19	1.50
Worst Drawdown	0.06	0.02
Average Drawdown	0.00	0.00
Skewness	-0.68	-0.32
Kurtosis	13.92	5.40

TABLE 7.5: Constrained MV Portfolio - Performance Metrics

7.3.4 Equal Risk Contribution

The last portfolio construction method investigated is ERC. As for the minimum variance portfolio, we constructed two distinct portfolios. The first, is unconstrained, and the second is constrained to the same weights our constrained minimum variance portfolio. As we have already defined the equal risk portfolio problem in Chapter 3. we focus on presenting our results. The portfolio weights were obtained using R's DeOptim library. The cumulative return lines, and performance statistics of both portfolios are presented next.

Unconstrained

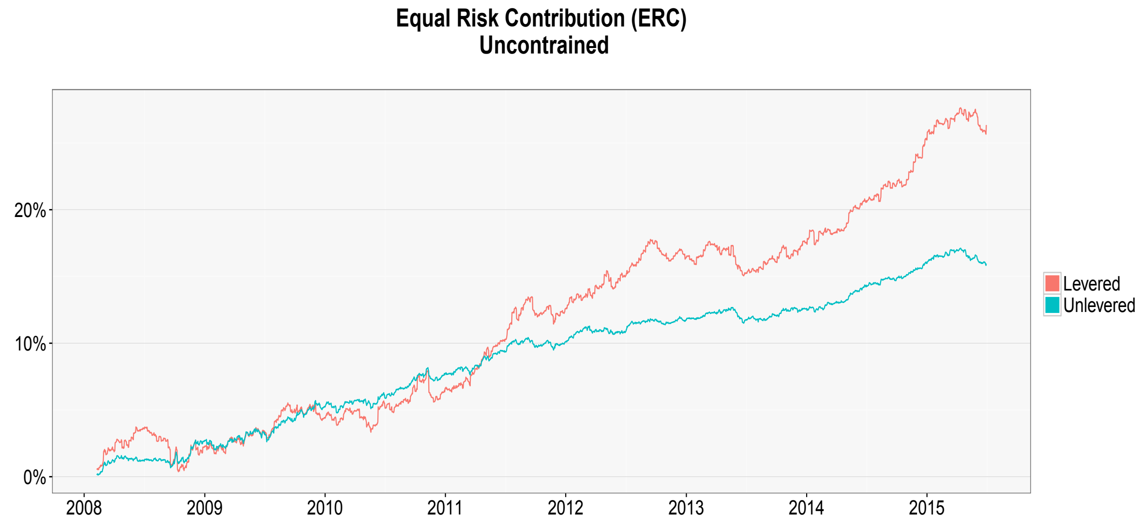

FIGURE 7.5: Unconstrained ERC Portfolio - Performance

	Levered	Unlevered
Cumulative Return	0.26	0.16
Annualized Return	0.03	0.02
Annualized Standard Deviation	0.02	0.01
Annualized Sharpe Ratio (rf=0%)	1.27	1.54
Worst Drawdown	0.03	0.01
Average Drawdown	0.00	0.00
Skewness	-0.68	-0.08
Kurtosis	16.40	6.08

TABLE 7.6: Unconstrained ERC Portfolio - Performance Metrics

Constrained

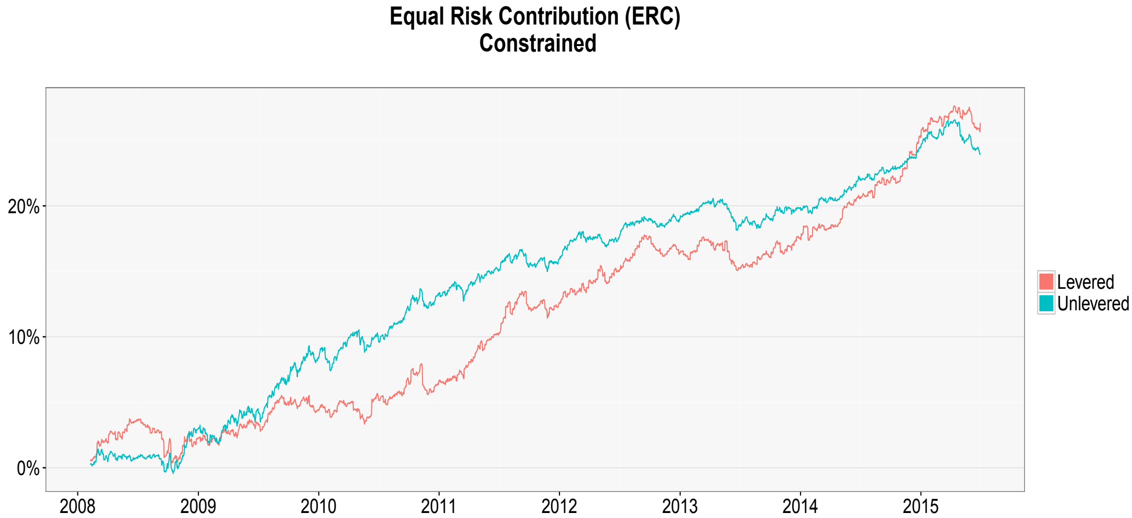

FIGURE 7.6: Constrained ERC Portfolio - Performance

	Levered	Unlevered
Cumulative Return	0.26	0.24
Annualized Return	0.03	0.03
Annualized Standard Deviation	0.02	0.02
Annualized Sharpe Ratio (rf=0%)	1.27	1.34
Worst Drawdown	0.03	0.02
Average Drawdown	0.00	0.00
Skewness	-0.68	-0.18
Kurtosis	16.40	5.38

TABLE 7.7: Constrained ERC Portfolio - Performance Metrics

7.4 Results Analysis

We conclude this chapter by discussing the results of our investigations. The equity line for our different risk premia portfolios (levered) are presented in the figure below. A visual examination of the results reveal that, as expected, the equal risk contribution portfolios are squeezed in between the equal weighted portfolio and the minimum variance portfolio (unconstrained). This is an interesting and encouraging result in itself as equal risk contribution portfolios are considered by certain authors' a trade-off between the equally weighted and minimum variance portfolios [12]. The fact that this holds for alternative risk premia as well means that the other properties of this method might also apply.

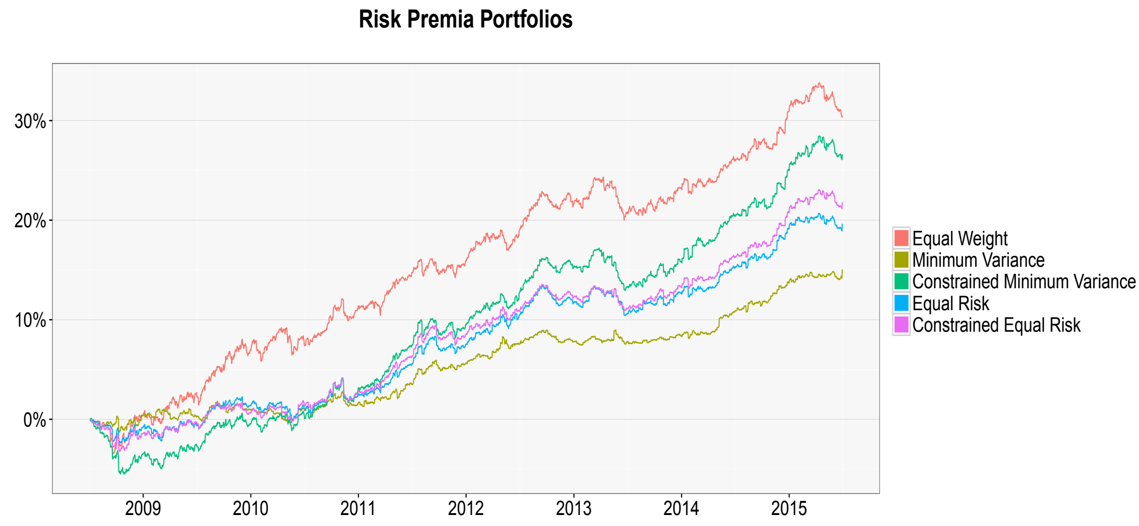

FIGURE 7.7: Portfolio Construction - Performance

	EW	MV	MV (Constrained)	ERC	ERC (Constrained)
Cumulative Return	0.31	0.15	0.27	0.20	0.22
Annualized Return	0.04	0.02	0.03	0.03	0.03
Annualized Standard Deviation	0.03	0.02	0.03	0.02	0.02
Annualized Sharpe Ratio (rf=0%)	1.24	1.06	1.19	1.07	1.14
Worst Drawdown	0.03	0.02	0.06	0.03	0.03
Average Drawdown	0.00	0.00	0.00	0.00	0.00
Skewness	-0.26	-0.29	-0.68	-0.84	-0.84
Kurtosis	8.17	21.20	13.92	16.12	17.04

TABLE 7.8: Portfolio Construction - Performance Metrics

The most surprising aspect of our results is the fact that the equal weighted portfolio delivered the best returns, and risk-adjusted returns (Sharpe ratio) over our sample period. This is discussed in detail next.

7.4.1 Performance Metrics

An analysis of the portfolios performance metrics reveal significant differences across the three different construction methodologies. First off, the equal weighted portfolio is the most attractive from a total return, but also from a risk to return perspective. Its dominance in Sharpe ratio terms is puzzling and warrants further investigation. A potential explanation may lie in the fact that alternative risk premia strategies exhibit low and stable correlations to one another. The equal weighted portfolio might somehow have benefited from this. There is also the fact that the other allocation methodologies faced significant transaction costs impacts. The equal weighted portfolio doesn't vary in weights, and therefore trades less than its counterparts. We will investigate this further in future works, but for the time being, we are reminded that equal weighted portfolios are more often than not, very difficult to beat in "real world" applications.

The following scatter chart shows each portfolio's risk to return positioning. The dotted grey lines represent Sharpe ratios of 1, 2 and 3. It is important to note that all our portfolios dominate the first line.

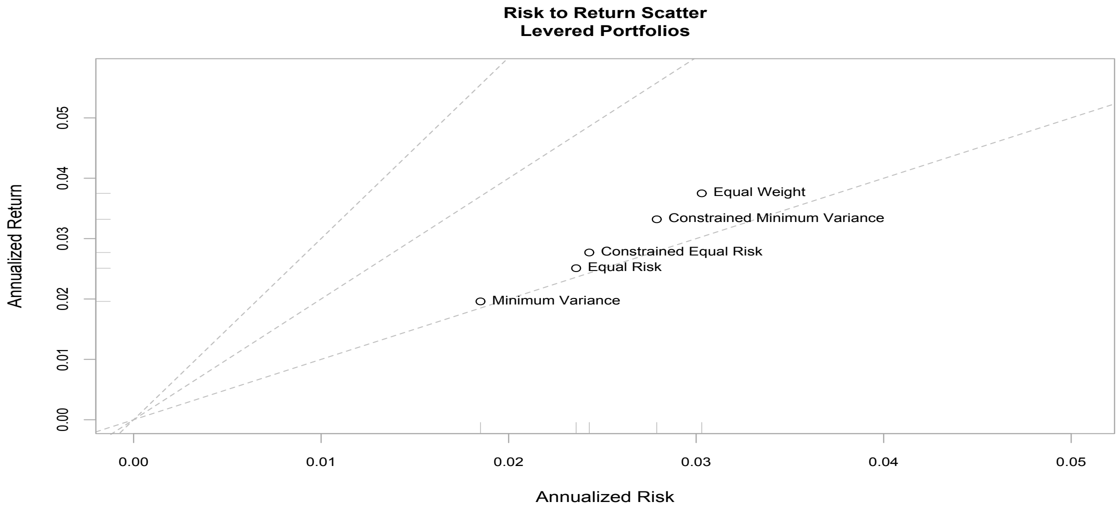

FIGURE 7.8: Portfolio Construction - Risk to Return Scatter

When assessing their drawdown profiles, we find that the the largest drawdowns belong to the constrained minimum variance portfolio. Although the volatility of this portfolio is lower than that of the equal weighted one, it still experiences a maximum drawdown that is 2.% higher. This can be observed in the figure below:

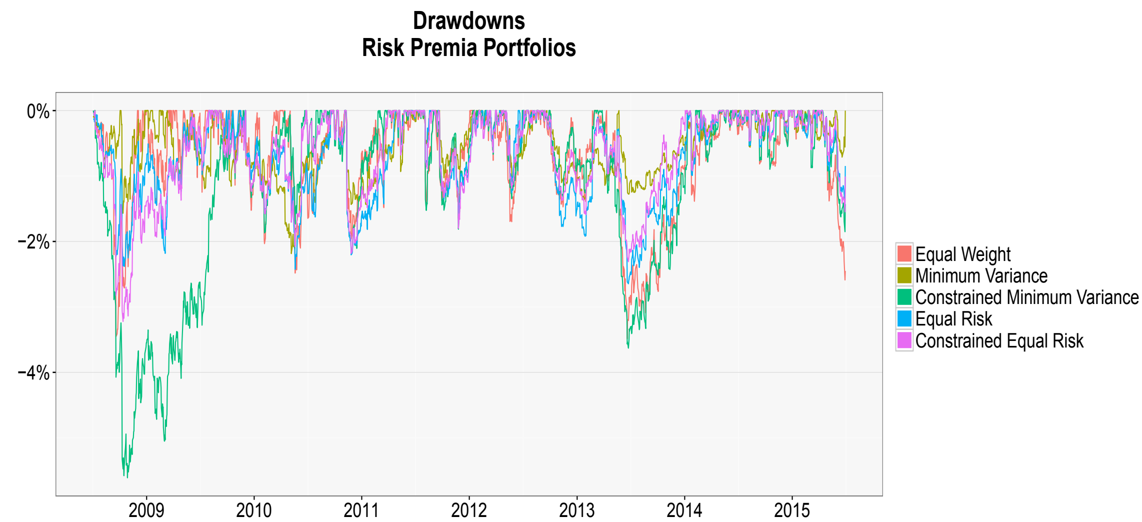

FIGURE 7.9: Portfolio Construction - Historical Drawdowns

We conclude this section by pointing to the fact that the skewness of all those portfolios are negative. This is expected from a "true" portfolio of risk premia strategies, and further strengthens our conviction in our results.

Chapter 8

Conclusion

8.1 Conclusion

The objective of this work was twofold. First, we demonstrated that a diversified set of alternative risk premia strategies could be accessed through futures contract trading. These strategies follow systematic trading signals and order sizing rules that can be implemented systematically. In contrast to many papers on the subject, we've deducted realistic trading costs from all our strategies. This is too often neglected and, as shown, it can have a significant impact on a strategy's returns. To mitigate the operational burden associated with trading those strategies, we've settled on a weekly rebalancing frequency for all of them. This was not always the most optimal choice, but it is one that we feel is much more realistic than assuming that investors (even institutional ones) always have the capabilities to trade on a daily basis. Institutional investors often think that to access these strategies, one needs to be trading a lot. We've dispelled this myth by showing that rebalancing the strategies and portfolios once a week, still allows one to capture the returns associated to these risk premia.

Secondly, we've demonstrated the importance of portfolio construction in aggregating these strategies together. The resulting portfolios are significantly impacted by the choice of portfolio construction. Unexpectedly, using our set of strategies and for the period studied, the equal weighted portfolio allocation provides investors with the most attractive risk to return profile. This is encouraging as this method is very intuitive to implement. It is possible that the other portfolio construction methodologies we have tested would have benefited from a different parametrization. We hope to test this in our future works.

An important finding associated to this research is the fact that, in the presence of transaction costs, even when applying a leverage factor on a weekly basis, we failed to achieve our annualized volatility target of 5%. Most portfolios undershoot it significantly. We will dedicate our future research toward solving this issue. A better understanding of the interactions between the leverage factor, the rebalancing frequency, and the portfolio construction method, should help us reach this target, even in the presence of transaction costs. This will be crucial for the real world investing applications of these portfolios.

The results of this research are but a stepping stone for further research on risk premia strategies. There is still much more to learn on the impact of the choice of portfolio construction methodologies on alternative risk premia portfolios. For instance, determining the performance of these portfolios under different market regimes is something that we hope to research next. We'll also explore the potential for these strategies to be used as alternative factors on which to regress hedge fund portfolios. This could help us better understand the underlying drivers of hedge fund performance, and in doing so, identify suitable research paths by which to improve the current state of hedge fund statistical replication methods.

Finally, we haven't discussed the appropriateness of these portfolios in a liability driven investment setting. We've demonstrated the attractiveness of their Sharpe ratio, and therefore expect them to be good candidate portfolios for LDI investors seeking an alternative to a pure bond exposure. This is another important path to explore. The research on alternative risk premia investing is still in its infancy, but as academic researchers and market practitioners start increasingly focusing on the subject, their increased adoption should provide us with important empirical and anecdotal data points. We can't help but feel that in time, these portfolios will replace the classic pension benchmarks, just as recently "Risk Parity" portfolios are slowly becoming the baseline for many of these investors.

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