Università
Ca'Foscari
Venezia

Master's Degree in Economics and Finance

Final Thesis

Does blending Alternative Risk Premia strategies improve portfolio performances?

Supervisor:
Marco Corazza

Graduand:
Marco Sartori
870000

Academic Year:
2019/2020

Abstract

For many years, academic literature have celebrated the usage of Alternative Risk Premia strategies (ARPs) to enhance overall portfolios performances. However, some authors have recently stated that in the last decade the benefits obtained through their implementation have decreased. In this thesis, I want to investigate how profitable have been these kind of portfolios during the years. In order to do so, I will create risk premia strategies portfolios for a wide range of asset classes and I will blend them in global multi-factor portfolios making use of several asset allocation methods. The analysis will not only provide an overview of the return and risk performances with respect to a traditional 60/40 benchmark, but it will also examine portfolios' sensitivity to different macroeconomic variables.

Contents

List of Figures

List of Tables

Chapter 1

The rise of Factor Investing

In this chapter I will introduce factor investing by describing the migration from traditional investing, which have long dominated the asset management industry, to the employment of risk premia in the pursuit of diversification and optimal risk-adjusted returns. After the first research on the topic, factor investing has started becoming accepted in both academic and industry environment producing astonishing theoretical excess returns. However, the spread of the approach through the public has revealed critical implementation challenges which must be considered when assessing theoretical performances.

1.1 From Traditional to ARPs

For several years, the dominant approach to investing was to allocate capital by asset class, obtaining diversification through exposure to equities, bonds and money market instruments. Notwithstanding stocks and bonds are generally considered weakly correlated, it was noted that during financial crises the correlation among asset classes spiked, thereby nullifying the diversification benefits. To this extent, many private and institutional investors started including alternative asset classes in their portfolios, such as commodities, currencies, real estate, private equity and hedge funds. Unfortunately, also these new assets provide only partial adequate diversification. The reason stems from the fact that some of them still remain too exposed on traditional asset classes. For instance, in their research Asness et al. (2001) founded that hedge funds who performed long/short equity strategies were as exposed to stock market risk as an S&P500 index fund. In the aftermath of the last global financial crisis in 2008, a different approach called 'Factor Investing' has started gaining consensus. The underlying idea is that investors are better off through investing in multiple risk premia rather than in the solo equity risk premium (Bhansali (2011)).

Defined a risk premium as the expected compensation earned by the investor for the systematic risk borne, Bender et al. (2009) categorize three types of premia. The first one is the ordinary asset class risk premium, which is the compensation earned in excess of the risk-free rate in a traditional source of risk such as equities or bonds. Then there is the style – or factor – risk premium, which is the systematic return coming from individual security characteristics like book-to-price ratio of equities or credit spread of fixed income securities. It is not in excess of the risk-free rate as the previous type, but instead is in excess of the broad asset class premia. Examples are the value and the momentum premia investigated by Bender et al. (2009) and Carhart (1997) in equities, which I will cover later. The last type is the strategy risk premium, which derives from replicating investment strategies. An example is the merger arbitrage strategy where the manager invests in the target and shorts the acquirer. In addition to the idea that factors earn excess returns because of the systematic risk attached to them, there is another doctrine which states that factors produce superior returns because of investors' systematic errors due to cognitive or emotional weaknesses (Bender et al. (2013)).

An extension of Factor Investing is the concept of 'Alternative Risk Premia' (ARPs). Unlike traditional risk premia, commonly referred as 'Smart Beta', which can be harvested passively from long-only exposures in conventional asset classes such as stocks and bonds, ARPs are dynamic and systematic sources of return gathered by using complex long-short market-neutral strategies. An example is the so called dollar-neutral strategy, where the long side is completely offset by the short side in dollar notional terms, that is managers buy and sell simultaneously an equal dollar amount of assets. A more intricate strategy is the beta-neutral strategy, which targets a zero total portfolio beta by aligning the beta of assets bought and the beta of assets sold short. The advantages provided by the composition of long-short portfolios are intuitive: they are able to capture pure factor premiums and to facilitate diversification removing the market exposure and improving risk-adjusted performances with respect to traditional approaches. For instance, let us suppose that an investor decides to take a long position in company X and a short position in company Y, both in the banking sector. Any adverse event for the banking sector would lead to a loss on the company X position and a profit on Y position. The opposite would occur in case of a positive event that causes both stocks to rise. In any case, the two positions balance each other out, so that the resulting market risk is minimal. The net effect, in the long run, will be a profit/loss if the investor's long side outperform/underperform its short side.

1.2 Academic Literature

Although the spread of the risk factor approach among the public has started recently, there are some institutional investors, such as Quantitative managers, Global Tactical

Asset Allocation (GTAA), Commodity Trading Advisors (CTAs) and Global Macro Hedge Fund managers, who pioneered it long before (Kolanovic and Wei (2013)).

Initially, academic literature focused solely on traditional equity risk premia. The first prominent model which included a risk factor was the 'Capital Asset Pricing Model' (CAPM), contributed by Treynor (1961), Sharpe (1964), Lintner (1965) e Mossin (1966). The model can be defined by the relationships:

$$E[R_i] - R_f = \beta_i^m (E[R_m] - R_f) \tag{1.1}$$

$$\beta_i^m = \frac{cov(R_i, R_m)}{\sigma^2(R_m)} \tag{1.2}$$

where R_i and R_m are respectively the asset and market returns, R_f is the risk-free rate, the coefficient β_i^m is the sensitivity of the i^{th} asset with respect to the market portfolio and $E[R_m] - R_f$ is, actually, the market factor. In the CAPM, securities have two drivers: systematic risk and idiosyncratic risk. Systematic risk, captured by beta, is the risk which arises from exposure to the market and, contrary to idiosyncratic risk, cannot be diversified away. Thus, investors are compensated with excess returns for bearing this type of risk.

A decade later Ross (1976) proposed an alternative to the CAPM called 'Arbitrage Pricing Theory' (APT), where expected return of a financial asset can be modelled as a linear function of various macroeconomic factors (like surprises in inflation, growth, shifts in the yield curve and so on) or theoretical market indices (like diversified stock indices as the S&P500, influential commodities prices or currencies exchange rates) instead of just one market factor. This can be considered as the first multi-factor model. Since then, academic literature has focused on the research of significant factors which have been persistent.

The most influential multi-factor model was conceived by Fama and French (1993). The model is an extension of the CAPM, where size risk and value risk factors are added to the pre-existing market factor. The size risk premia (SMB) captures excess returns of smaller firms (by market capitalization) relative to their larger counterparts, while the value risk premia (HML) describes excess returns to stocks that have low prices relative to their fundamental value. The new relationship can be represented as:

$$E[R_i] - R_f = \beta_i^m (E[R_m] - R_f) + \beta_i^{SMB} E[R_{SMB}] + \beta_i^{HML} E[R_{HML}] \tag{1.3}$$

where R_{SMB} is the return of small stocks minus the return of large stocks and R_{HML} is the return of stocks with high book-to-market values minus the return of stocks with low book-to-market values. Further improvements were included in this three-factor model later. Noteworthy are the inclusion of the momentum factor by Carhart (1997), which set a standard in finance literature and the more recent Fama and French's five-factor model published in 2016, where they added profitability and investment factors (Fama and French (2016)).

1.3 Issues with Factor Investing

Although factor investing works in theory, some problems arise when it comes to implement strategies in practice. In a recent paper, Arnott et al. (2019) listed a series of blunders which have affected investors' expectations on risk premia strategies.

First of all, the question of which factors actually matter. Figure 1.1 provides the results of the updated analysis conducted by Harvey and Liu (2019) about the amount of factors documented in top-tier academic journals. In their research, they counted almost 400 published factors claimed to be statistically significant. However, some of them would seem profitable in the back-test by chance because standard significance levels are not appropriate and do not consider multiple trials and testing. This thesis focuses on the most widely known and broadly tested sources of returns like value, carry, momentum and volatility.

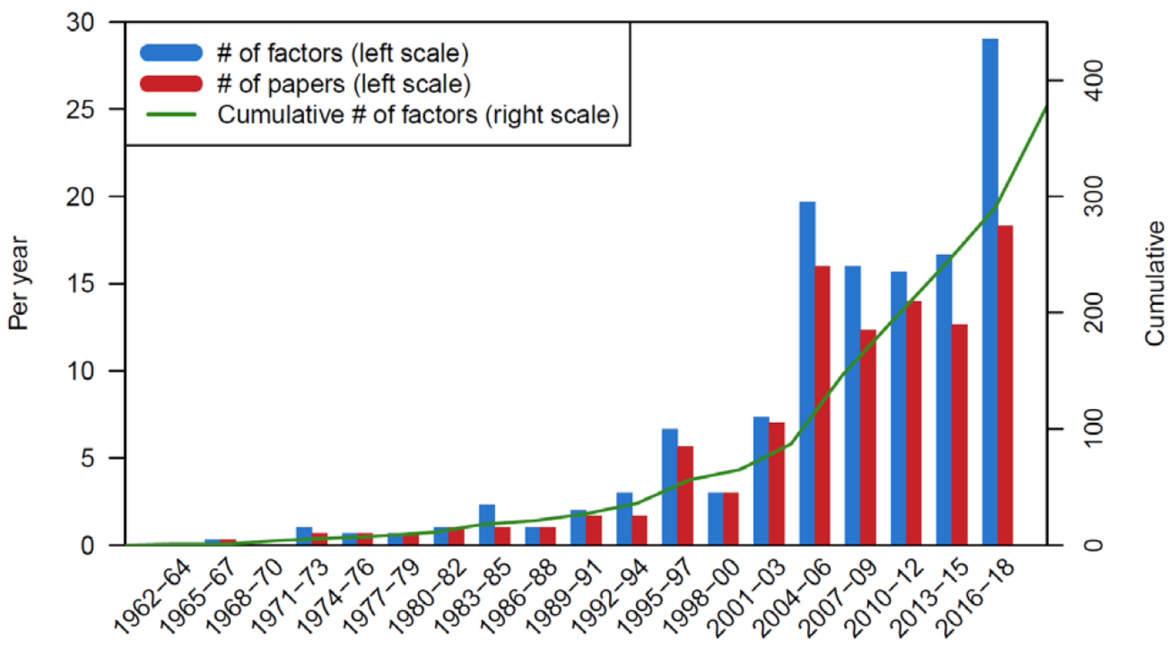

Figure 1.1: Factors and Publications. *Source: Harvey and Liu (2019)*

But even if a factor has a true structural risk premium, real-world returns can disappoint once the factor becomes crowded. In their article, Arnott et al. (2019) measured factor performances before and after the end of the sample period used in the original study that discovered each factor. As shown in Figure 1.2, they found that factor performances displayed a break point at the end of the in-sample period, when average returns started to decrease with respect to average returns over the 10 years prior to this date (the break point period). The results are consistent with another study conducted by McLean and Pontiff (2016), in which they found that after the discovery of a factor, investors try to exploit the anomaly leading the average factor's return to decay by about 32%.

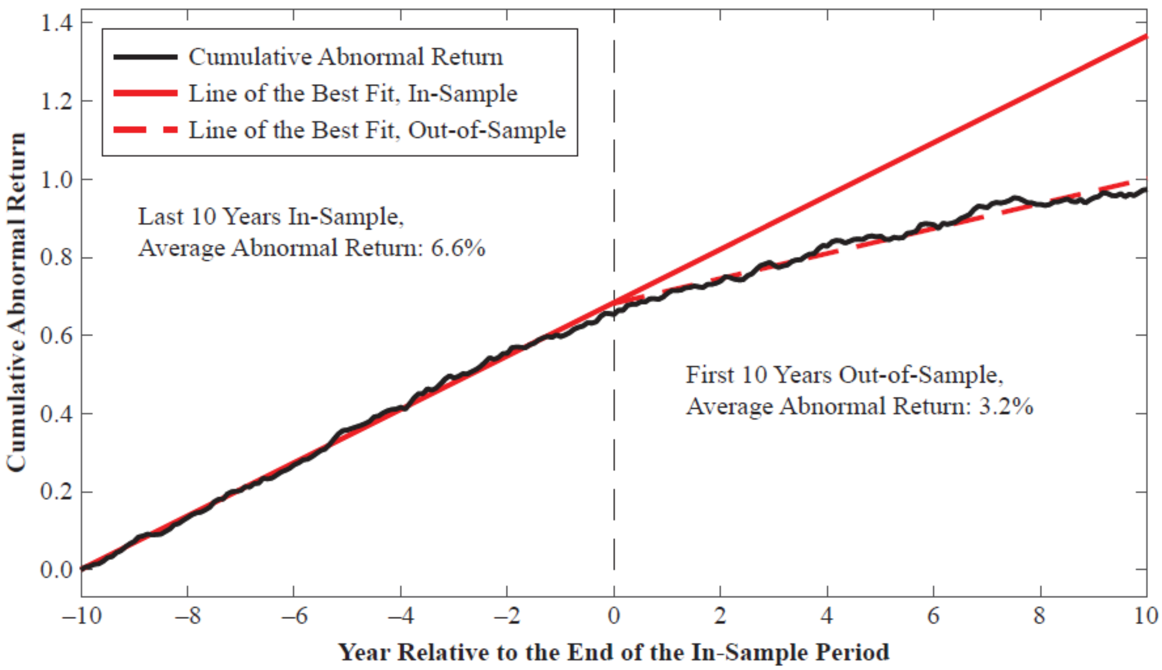

Figure 1.2: Cumulative performance before and after Publication. *Source: Arnott et al. (2019)*

Another blunder with factor investing is that investors usually assume factor returns to be normally distributed and this lead to underestimate the frequency of large drawdowns using simple risk management, which ignore tail features. Given that most risk factors have excess kurtosis (fat tails) and negative skewness, it means that the probability of sizeable negative events is actually greater than what it would be if estimated using standard normal distribution.

The last issue is relative to constraints and implementation costs. Bambaci et al. (2013) pointed out three investability limits:

- Constraints on short position: theoretical factor portfolios are based on long-short portfolios with no constraints on the size of short positions. In practice, a limit on short selling is generally imposed.

- Monthly rebalancing: theoretical factor portfolios are rebalanced monthly, which means the turnover is considerably higher than for institutional benchmarks, generally rebalanced yearly. When transactions costs are not properly estimated or (worse) ignored, an overestimation of these factor portfolios performances may occur.

- Small caps restrictions: theoretical factor portfolios usually include small caps in their composition. In practice, large funds and institutional investors are often constrained from investing in certain stocks, due to small size and reputation, making it impossible to replicate a theoretical portfolio.

Chapter 2

Risk Strategies

In this chapter I will define the four risk premia strategies selected for the research and provide the rationale for their existence. Some guidelines about the methodology will be offered too, in particular how to quantify the magnitude of each risk measure and how to compose the long/short factor portfolio for each asset class.

2.1 Value

2.1.1 Definition

One of the oldest and best known selection approaches is value investing. It is based on the assumption that assets have a tendency to mean revert around a fundamental value when considered cheap or expensive. To capture the value premium, the idea is to take a set of assets, sort them using some measures of value (for example the inverse of the P/E ratio for stocks) and go long (or overweight) the assets with high value measures ratios and short (or underweight) the assets with low ones.

The strategy has a long history. Since Graham and Dodd (1934), famous practitioners (such as W. Buffett) has implemented value in their investment methods. However, the topic caught strong academic attention in the early 1990s with the aforementioned seminal Fama-French publication. Initially the attention was paid exclusively to US stocks, but later studies (Chan et al. (1991), Fama and French (1998), Malkiel and Jun (2009) and Asness et al. (2013)) confirmed value premium in different markets and asset classes. As anticipated in chapter 1, the existence of these risk premia can be due to both risk-based explanations and behavioural biases. From the point of view of supporters of the first cause, value premium exists because value stocks are riskier than growth stocks, due to high financial leverage, volatile future earnings and greater sensitivity to economic shocks (Chen and Zhang (1998), Winkelmann et al. (2013)). From the viewpoint of behaviourists, it may be caused by excessive extrapolation of growth trends and delayed overreaction to information (Lakonishok et al. (1994)).

2.1.2 Methodology

The value measure differs among asset classes. While for stocks we can use the ratio of the book value of a company relative to its market price (or earnings, cash flows, sales, dividends to price), for bonds, currencies and commodities other kind of fundamental measures which do not derive from accounting statements are required.

The methodology used in this thesis is similar to the one proposed by Asness et al. (2013):

- For equity indices, the inverse of the previous month's P/E ratio for the MSCI index of the country.
- For bonds, the 5-years change in the yields of 10-years bonds.
- For currencies, the negative of the 5-years return on the exchange rate, measured as the log of the average spot exchange rate from 4.5 to 5.5 years ago divided by the spot exchange rate today minus the log difference in the change in CPI (Consumer Price Index) in the foreign country relative to the U.S. over the same period. This is essentially the 5-year change in PPP (Purchasing Power Parity).
- For commodities, the negative of the spot return over the last 3 years computed as the log of the spot price 3 years ago divided by the most recent spot price. Given the unavailability of reliable spot prices for commodities, I will use the front month futures prices as spot prices. The 3-years change return is a value measure motivated by DeBondt and Thaler (1985), who showed the presence of price reversals at a horizon of three to five years, so that buying past losers and sell past winners produced positive returns.

After having computed a value measure for each security within each asset class, we sort and rank them in ascending order. Now we can form the zero-cost long/short value portfolios introduced in chapter 1 for every single asset class. Recall that the term "zero-cost", or dollar-neutral, indicates that the cash obtained by selling securities with low signals offsets the long position of securities with high measures.

For any security $i = 1, ..., N$ at time t with value measure $V_{i,t}$, the weight is computed as:

$$w_{i,t} = z_t(rank(V_{i,t}) - \frac{N+1}{2}) \tag{2.1}$$

$$z_t = \frac{2}{\sum_{i=1}^{N} |rank(V_{i,t}) - \frac{N+1}{2}|} \tag{2.2}$$

where z_t is a normalizing constant which ensures that the sums of the long and short exposures are respectively $+1$ and -1.

The return on the value portfolio (asset class specific) is the weighted sum of individual returns:

$$r_{p,t+1}^{VAL} = \sum_{i=1}^{N} w_{i,t} r_{i,t+1} \tag{2.3}$$

At this point, to get a value portfolio which is diversified across asset classes, an additional step must be taken. Asness et al. (2013), Koijen et al. (2018), Moskowitz et al. (2012) and many others suggest blending the four asset class specific value portfolios through equal-volatility weighting, or inverse volatility weighting. This is motivated by the need to avoid that the risk generated by return strategies within asset classes historically proven more volatile (commodities and equities) would dominate the overall portfolio risk. I will adhere to this recommendation but, at the same time, I will generate five additional global value portfolio through various asset allocation methods (all describe in the chapter 3).

2.2 Carry

2.2.1 Definition

Another strategy which has produced consistent returns over time is carry. It is based on investing in higher yielding assets while financing the position by shorting lower yielding assets. A standard definition is given by Koijen et al. (2018), who defined an asset's carry as "its future return, assuming that prices stay the same". To make it clearer, they decomposed a security's return into the following blocks:

$$\text{Return}_{t+1} = \underbrace{\text{Carry}_t + \text{Expected price appreciation}_{t+1}}_{\text{Expected return}_{t+1}} + \text{Unexpected price shock}_{t+1} \tag{2.4}$$

They argued that while expected price appreciation must be estimated using an asset pricing model, carry has the advantage to be a model-free characteristic directly observable ex ante from futures (or synthetic futures) prices.

Historically, carry strategies have been related to currencies only. The classic approach has been sorting countries by their short-term rates and taking long positions in currencies of the countries with the highest interest rate and taking short position in currencies of the opposite countries. The existence of a long history of positive returns is a clear violation of the uncovered interest rate parity (UIP) condition, which states that the interest rates differential between two countries should equals the expected depreciation of their currency exchange rates. The breaking of the law may be caused by the presence of non-profit-seeking market participants, such as central banks, who may introduce inefficiencies for short horizons into currency markets and interest rates (Asness et al. (2015)), or may represent compensation for exposure to consumption risk (Lustig and Verdelhan (2007)), crash risk and liquidity risk (Brunnermeier et al. (2008), Burnside et al. (2011)).

Nevertheless, carry can also apply to other asset classes and the methodology will be explained extensively soon. In fixed income, carry strategies can be sought by buying the developed market government bonds with the highest yield and selling those with lowest yield. In commodities, it can be useful to utilize the slope between the nearest and second-nearest to maturity futures contracts and overweight the commodities with the strongest backwardation (downward slope) and underweight those with strongest contango (upward slope). Finally, carry strategies can also be applied to the equity market by considering the dividend yield; in this last case, the factor has been proved to be highly correlated to the equity value factor (Maeso and Martellini (2017)).

2.2.2 Methodology

So how to compute a carry measure for different type of assets? The appropriate methodology is given in the research conducted by Koijen et al. (2018) mentioned above. The general formula for the carry of a fully collateralized position is:

$$C_t = \frac{S_t - F_t}{F_t} \tag{2.5}$$

where S_t is the spot price of the underlying security and F_t is the current future price of a contract which expires at maturity $t+1$. This formula can be transformed depending on the asset class considered.

I want to start from the most traditional asset class used with carry strategies: currencies. Under the covered interest rate parity (CIP), the no-arbitrage price of a currency future contract with a spot exchange rate S_t (measured as local currency units per unit of foreign currency) and local and foreign short-term (3 months) interest rates being respectively r_t^f and $r_t^{f^*}$, must satisfies the following equation: $F_t = S_t(1+r_t^f)/(1+r_t^{f^*})$. Based on this relation, investors should be indifferent between investing in the local market or performing a carry trade by borrowing in the domestic market, lending in the foreign higher rate market and entering a futures contract to lock the future exchange rate (Jurczenko (2017)). Therefore, the carry for currencies can be measured as the spread between the two interest rates, adjusted for a scaling factor closed to one:

$$C_t = \frac{S_t - F_t}{F_t} = \frac{r_t^{f*} - r_t^f}{1 + r_t^f} \tag{2.6}$$

The scaling factor $(1 + r_t^f)^{-1}$ represents the discount effect incurred today by using a future contract, which implies the purchase of a unit of foreign currency at time $t + 1$.

Carry for equity indices can be found in a similar fashion. The no-arbitrage price for a futures contract is $F_t = S_t(1 + r_t^f) - E_t^Q(D_{t+1})$ where S_t and r_t^f are still the currently value of the underlying and the local interest rate (referred to the country of the equity index) and $E_t^Q(D_{t+1})$ is the expected future dividend payment computed using the risk-neutral measure Q. As a consequence, the equity carry can be written as:

$$C_t = \frac{S_t - F_t}{F_t} = \left(\frac{E_t^Q(D_{t+1})}{S_t} - r_t^f \right) \frac{S_t}{F_t} \tag{2.7}$$

In this case, the scaling factor is the ratio between the current spot price and futures price and, as before, is close to one. Note that a suggestion for the usage of dividends yields was advanced for equity value measures too. The two dividends yields are related but not equals; in fact, while for the equity value strategy realised (backward-looking) dividend yields are used, for the equity carry approach we focus on expected (forward-looking) dividend yields. However, this usually leads to a certain level of correlation between the two strategies, relative to equities asset class. Tough this last formula is the one suggested to compute the measure for equity indices, I will stick to the more general initial formula which requires only spot and nearest to maturity futures prices. This is imposed by the difficulty of finding long-enough reliable data series on expected dividends.

For commodity futures contracts, the no-arbitrage condition is $F_t = S_t(1+r_t^f - \gamma_t)$ where γ_t is the expected convenience yield in excess of storage costs. The convenience yield is the premium obtained when holding a certain underlying product. For example, in case of sudden drought of a resource, the short-term demand for the security may overcome its actual supply, creating an advantage for the holder of the physical good. This is opposed to the cost of holding the underlying, which is called storage cost. Rearranging the equations, the commodity carry should result in the expected convenience yield in excess of the prevailing risk-free rate, adjusted for a scaling factor close to one:

$$C_t = \frac{S_t - F_t}{F_t} = (\gamma_t - r_t^f) \frac{S_t}{F_t} \tag{2.8}$$

However, as already mentioned, challenge occurs with commodities as their spot markets are illiquid and lack of reliable spot prices. The problem of comparing the spot price with the first nearby futures price can be circumvented by using the slope between the nearest and second-nearest to maturity future contracts. Hence, being F_t^1 and F_t^2 respectively the nearest and second-nearest to maturity futures prices with T_1 and T_2 months to maturity ($T_1 < T_2$), we can rearrange the commodity carry of holding the second-nearest contract, assuming that the spot price will converge to F_t^1 after $T_2 - T_1$ months, as:

$$C_t = \frac{F_t^1 - F_t^2}{F_t^2} = (\gamma_t - r_t^f)\frac{F_t^1}{F_t^2} \tag{2.9}$$

Thus, the more backwardated is a contract ($F_t^1 > F_t^2$), the more carry yield it is expected to provide. To take advantage of this measure while further smoothing the portfolio performance, a trading technique called calendar spread is applied. The strategy involves buying a derivative of an asset in one month and selling a derivative of the same asset in another month. When carry is positive, a long position in the second-nearest futures contract and a short position in the nearest to maturity contracts are taken.

Finally, the carry of bond futures, which is computed simply considering the 10-years term spread (10-year yield minus 3-month interest rate) of each bond security. This is similar to what proposed by Koijen et al. (2018).

The process to form the asset class specific carry portfolios, to compute their returns and to form the global carry portfolio diversified through asset classes is similar to the one for the value strategy. The lone exception is the computation of the commodities carry portfolio return. As each security entails simultaneously long and short position on contracts with different maturities, its return contribution to the total portfolio is formed considering the profit/loss generated from the calendar spread. If $r_{LP,t}$ and $r_{SP,t}$ are respectively the returns produced by the long and short positions taken in each commodity, the commodities carry portfolio return is computed including equation 2.10 as:

$$r_{i,t} = r_{LP,t} - r_{SP,t} \tag{2.10}$$

$$r_{p,t+1}^{CAR} = \sum_{i=1}^{N} w_{i,t} r_{i,t+1} \tag{2.11}$$

2.3 Momentum

2.3.1 Definition

The next strategy implemented in this thesis is momentum. I have already mentioned it as the extension applied by Carhart (1997) to the prominent Fama-French's three-factor model, but one of the first papers on momentum was published by Jegadeesh and Titman (1993). In their research, they reported evidence of return predictability in equity markets based on past returns and argued that buying stocks that have performed well over the past three to twelve months and selling stocks that have performed poorly produces abnormal positive returns. Despite the fact that this effect goes against the hypothesis of efficient markets broadly accepted during those years, it has produced astonishing excess returns across different asset classes over the years (Moskowitz et al. (2012)). In particular, outstanding positive returns have been harvested in small cap and emerging equity markets and, in particular, in commodities.

The common belief of considering momentum as a 'market anomaly' may be due to the numerous behavioural theories advanced to explain its existence. The most relevant thesis associate momentum to the investors tendency to underreact and overreact to new information at a different speed, or to anchoring, that is when individuals depends too heavily on initial piece of information, or mislead information (Hong and Stein (1999)). But these patterns can be reinforced also by herding behaviour, that is when investors follow what other investors are doing without acting under what their own analysis suggest. Finally, the disposition effect, which is the tendency to sell winners too soon and secure minimal profits (being afraid to lose the possibility to earn from the investment) and to hold on losers too long, waiting for the price to turnaround (Frazzini (2006)). Closely related to behavioural theories are the ones connected to the market micro-structure, where investors employ products that mirror their behavioral biases. For instance, the implementation of particular trading strategies enhance momentum by committing investors to sell underperforming assets and to buy outperforming ones in advance (Kolanovic and Wei (2013)). An examples is the stop-loss strategy, where investors promptly switch their position from risky assets, such as stocks, to risk-free assets or cash after that pre-determined cumulative losses occur, enhancing the trend in place.

There are two types of momentum: cross-sectional and time-series. While they both select assets on the basis of their past performance, the first approach assigns assets to the winner and loser portfolio on the basis of their relative performance while the second approach assigns assets on the basis of their absolute performance. Usually, cross-sectional strategies impose that the notional amount of the long side of the portfolio must offset the short side (dollar-neutral, like value and carry portfolios formed in this thesis) or that the beta amount of the long side is offset by the beta of the short side (beta-neutral, like the volatility portfolios described next), but time-series strategies do not entail such constraints. A recent paper by Bird et al. (2017) compares the two strategies for a universe of stock indices and concluded that time-series momentum is more profitable in the long run than cross-sectional momentum, even though it must be said that they both acted positively. Because of these results, I will use the time-series approach and, to do so, I will adhere to the well-known research conducted by Moskowitz et al. (2012) on a wider range of assets (equities, bonds, currencies and commodities).

2.3.2 Methodology

The momentum measure suggested is the simplest and most standard measure, common for all the asset classes involved: the 12-month cumulative raw return skipping the most recent month's return, to avoid the 1-month reversal related to liquidity or micro-structure issues.

$$M_{t,h} = \frac{P_{t-1} - P_{t-h}}{P_{t-h}} \tag{2.12}$$

where P_{t-h} is the asset price delayed by a momentum period h, which is usually 12 months, in case of monthly data.

To arrange the asset class specific momentum portfolios, I refer to the Moskowitz et al. (2012) procedure where a long/short portfolio is formed considering any security $i = 1, ..., N$ at time t with momentum measure $M_{i,t}$.

$$I_{i,t} = \begin{cases} +1 & \text{for } M_{i,t} > 0 \\ -1 & \text{for } M_{i,t} \leq 0 \end{cases} \tag{2.13}$$

where $+1$ corresponds to a long signal and -1 a short signal.

The return on the momentum portfolio (asset class specific) is the weighted average of individual returns:

$$r^{MOM}_{p,t+1} = \frac{1}{N} \sum_{i=1}^{N} I_{i,t} r_{i,t+1} \tag{2.14}$$

Finally, to get the global momentum portfolio diversified across asset classes, I follow the same approach described in the value section.

2.4 Volatility

2.4.1 Definition

The last strategy I want to investigate is the defensive strategy, which attempts to capture the so-called 'low volatility anomaly'. The reason why the premium is considered an anomaly stems from the fact that it is in conflict with one of the most critical principles in finance, that is higher risk is associated with higher returns. The first author which observed this violation is Black (1972), who noticed that the security market line in US stocks (the link between market beta to its average returns) was flatter than the one predicted by the CAPM model. As a consequence, low-risk assets were relatively more profitable than their riskier counterparts. Further research have been conducted later on. Leading is the critique of capitalization-weighted benchmark advanced by Haugen and Baker (1991), who demonstrated how poorly those capitalization-weighted indexes performed relative to low volatility US stocks during the 1972 to 1989 period. Additional confirmations for the US market came from Chan et al. (1999), Jagannathan and Ma (2003) and Clarke et al. (2006) and, for global markets, from Ang et al. (2006) and Ang et al. (2009). Finally, a wider research which included several asset classes across global markets was conducted by Frazzini and Pedersen (2014).

One of the most accepted explanation for the low risk effect is the one considering leverage restrictions. A basic premise of the CAPM is that all the agents seek to invest in the portfolio of assets which produces the highest risk-adjusted return and to leverage or deleverage the portfolio in order to achieve the desired level of risk. Leverage is an investment style which use borrowed money to increase the potential return of an investment. The problem is that some of these investors may face limitations on this technique and thus decide to adjust the portfolio volatility by overweighting risky assets and underweighting safe ones. By doing so, returns on assets become 'biased', namely high risk securities generate lower than expected returns with respect to safe securities, compared to a situation where all individuals access leverage Frazzini and Pedersen (2014).

Other justifications are from a behavioural perspective. Bali et al. (2011) associated the tendency of overpaying risky stocks and underpaying safe stocks to the gambling behaviour where people are willing to accept high probability of small losses for minimal chances of earning superior returns. This is known as the 'lottery effect'. Bender et al. (2013) listed other less relevant behavioural effects:

- Representativeness, where the attractive performances of some well publicized risky stocks led investors to overestimate other volatile stocks.

- Asymmetric behaviour in bull/bear markets: during period of market distress low volatility portfolios experience softer drawdowns with respect to high volatility portfolios, but during market expansions the difference in performances are not so marked.

- Agency issue, where low volatility stocks are generally avoided by management because there is less attention and research support.

2.4.2 Methodology

Metrics used to harvest low volatility premium for stocks range along several options. For example, it can be used realized volatility, forecast volatility, correlations, beta or even more fundamental measures of risk, where safe stocks are gauged as the less exposed to macroeconomic oscillations, with high stable profitability, low leverage and so on (Frazzini et al. (2012)).

The methodology used to compose factors portfolios for all asset classes is similar to the procedure suggested by Frazzini and Pedersen (2014), where they considered the traditional definition of beta as metric. First of all, an estimation of each security' ex-ante beta is obtained from rolling regressions of excess returns on market excess returns. The rolling period should be selected as much long as possible to improve the quality of the estimation. However, choosing a long time windows may bias the estimation using data generated in different market environment. Based on these issues and considered the limited amount of data in possess for equities futures contracts, I decided to set the rolling window equal to 12 months. The beta is then computed as:

$$\hat{\beta}_{i,t} = \hat{\rho}_{im,t} \frac{\hat{\sigma}_{i,t}}{\hat{\sigma}_{m,t}} \tag{2.15}$$

where $\hat{\sigma}_{i,t}$ and $\hat{\sigma}_{m,t}$ are respectively the estimated volatilities at time t for the i^{th} security and the market and $\hat{\rho}_{im,t}$ is the estimated correlation at time t between the security and the market portfolio. The market portfolios to use in order to estimate betas are GDP or risk weighted portfolios for each asset class. To bypass the lack of consistent GDP/risk weighted benchmark portfolios, I decided to compose my own equal-volatility weighted benchmarks using each security available in each asset class.

As the estimated betas are obtained, portfolios which are long low-beta securities and short-sell high-beta securities can be constructed. The procedure is similar to the one used for the other cross-sectional approaches (value and carry). Broadly speaking, securities must be ordered in ascending order on the basis of their estimated beta and those with a beta below the asset class median value will be considered as low-beta assets (long position) and those with a beta above the median value will be counted as high-beta securities (short position).

However, the portfolio resulting by the process must be converted in a beta-neutral portfolio by scaling the beta of the low-beta portfolio to $+1$ and the beta of the high-beta portfolio to -1. To do so leverage is needed, but to avoid massive spikes and drops (especially for commodities), constraints on the leverage applied to low-beta portfolios are imposed. The strategies will scale returns to a maximum of 200% while limiting the minimum exposure to 100%.

Finally, a global volatility portfolio diversified within asset classes is formed with usual procedure.

Chapter 3

Allocation Methods

In this chapter I will introduce the theory of the asset allocation methods that will be employed to compose the global ARPs portfolios. As I will make clear in the next chapter, the different strategies analysed will be blended in a final unique multi-factor portfolio adopting various approaches ranging from the traditional mean-variance optimization to other more recent methodologies which benefit from less estimation error.

3.1 Mean Variance Portfolios

In 1952, a 25-years old Harry Markowitz published a paper called "Portfolio Selection" in which he introduced what is nowadays known as the Modern Portfolio Theory (MPT). His work (Markowitz (1952)) is not only considered a milestone in portfolio construction but granted him the opportunity to share a Nobel Prize with Miller and Sharpe, in 1990.

The main objective of the MPT is to create a set of efficient portfolios by accurately weighting a universe of assets in order to maximize the expected return, given the level of risk generated. In fact, Markowitz demonstrated that under certain assumptions the allocation problem can be reduced to a mean-variance optimization procedure and that, through diversification, we can lower the total portfolio risk without affecting significantly the total expected return. Some of these assumptions imply that investors are rational, have access to the same information and can borrow and lend money at a risk-free rate. Furthermore, they do not influence market prices and seek to maximize returns given their own personal utility function and risk aversion. Despite these assumptions are hardly achieved in the real world, the mean-variance optimization (MVO) has been massively used by investors and financial institutions when composing their portfolios.

Let start considering a universe of n risky securities, a vector of weights in the portfolio $w = (w_1, ..., w_n)$ and assume that the portfolio is fully invested, that is $\sum_{i=1}^{n} w_i = e^{'}w =$

1, where e is a column vector of n ones. Let us define the vector of individual rate of returns $R = (R_1, ..., R_n)$ and its expected value $E[R] = r = (r_1, ..., r_n)$, which both serve to derive the return of the portfolio $\sum_{i=1}^{n} w_i R_i = w^{'} R$ and its expected value:

$$E[R_P] = \sum_{i=1}^{n} w_i r_i = w^{'} r \tag{3.1}$$

Finally, we can obtain the variance of the portfolio as:

$$Var[R_P] = \sigma_P^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{i,j} = w^{'} \Sigma w \tag{3.2}$$

where Σ is the variance-covariance matrix, σ_i^2 is the variance of individual securities and $\sigma_{i,j} = \rho_{i,j} \sigma_i \sigma_j$ is the covariance between securities i and j, with $\rho_{i,j} \in [-1, 1]$.

At this point, we can solve the optimization in the following alternative ways. The first one is maximizing the expected return of the portfolio given a certain tolerable level of volatility σ_P^*. The second is to minimize the volatility of the portfolio given a certain requested level of return, r_p^*. For instance, in this last case the optimization problem is:

$$\begin{cases} \min\limits_{w} w^{'} \Sigma w \quad \text{s.t.} \\ w^{'} r = r_p^* \\ e^{'} w = 1 \end{cases} \tag{3.3}$$

The set of optimal portfolios generated by the optimization process for different values of r_p^* (or σ_P^*, if we follow the first alternative) composes what is called the efficient frontier, which is the blue curve in Figure 3.1. Every investor, considering his/her ideal expected return and/or risk aversion, will select one of the portfolios placed on it and will reject sub-optimal portfolios below and on the right of the curve because they do not provide enough return with respect to the risk attached.

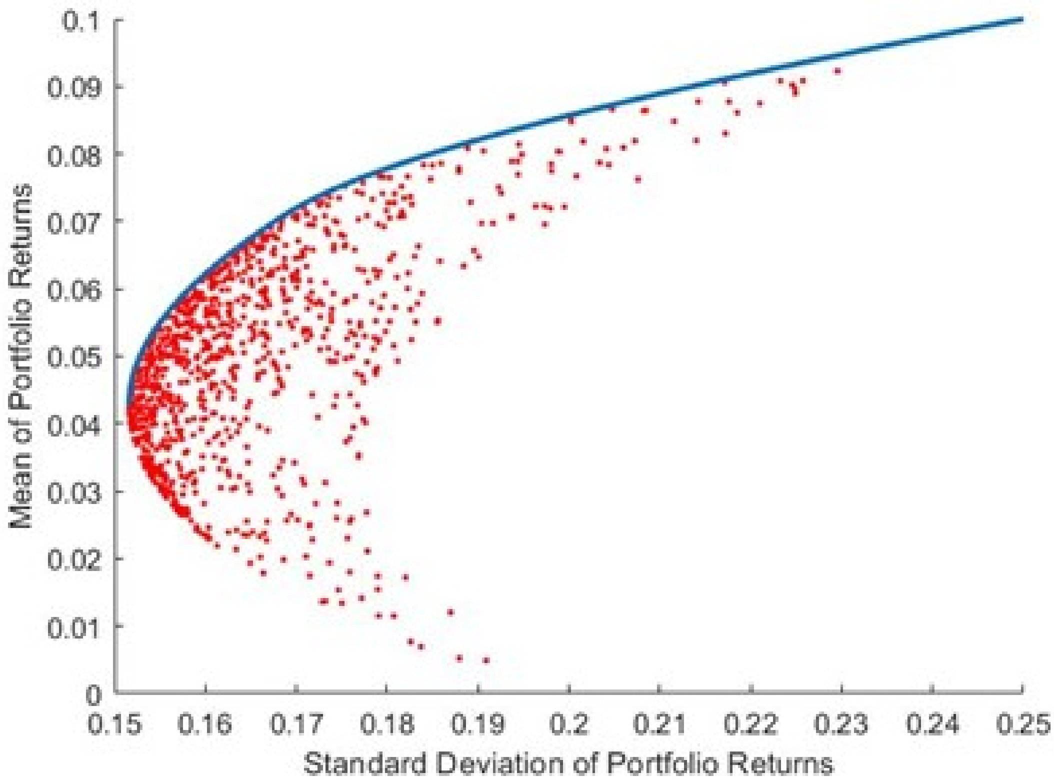

Figure 3.1: Sample portfolios and the Efficient frontier. *Source: Random simulation generated on Matlab*

This thesis will focus on two types of portfolio derived from the mean-variance framework: the global minimum variance portfolio and the maximum Sharpe Ratio portfolio.

3.1.1 Global Minimum Variance Portfolio

The global minimum variance portfolio (GMV) is graphically identified as the left-most component of the efficient frontier (Figure 3.2) and it is the portfolio whose assets' weights minimize the portfolio variance without being dependent on any prior assumption about r_p^*. It can be detected by solving the following optimization problem:

$$\begin{cases} \min\limits_{w} w^{'}\Sigma w \quad \text{s.t.} \\ e^{'}w = 1 \end{cases} \tag{3.4}$$

By using the Lagrange multiplier, we can solve the problem and obtain that the vector of optimal weights which minimizes the volatility is:

$$w_{GMV} = \frac{\Sigma^{-1}e}{e'\Sigma^{-1}e} \tag{3.5}$$

As already mentioned, this optimization procedure does not require to set a target required rate of return r_p^*. This is a crucial characteristic because the set of required estimated parameters is reduced to the sole variance-covariance matrix, thus lowering the chance of estimation error of the asset expected returns. In fact, Chopra and Ziemba (1993) asserted that errors stemming from the estimation of returns is one of the main explanations about why the mean-variance approach produces relatively poor performances in practice. Other "return free" methods exist in literature. Some of them, like the equally weighted portfolio and the risk parity portfolio, are considered in this thesis.

3.1.2 Maximum Sharpe Ratio Portfolio

The maximum Sharpe ratio portfolio (MSR) is another mean-variance based approach which select the portfolio in the efficient frontier with the highest Sharpe ratio offered. The Sharpe ratio was developed by the Nobel prize William F. Sharpe in 1966 (Sharpe (1966)) and is particularly useful to compare funds' performances as it measures the performance of an investment (r_p) compared to a risk-free option (r_f), adjusted for the risk generated (σ_p).

$$\text{Sharpe Ratio} = \frac{r_p - r_f}{\sigma_p} \tag{3.6}$$

This is the choice for investors who do not set preferences relative to required returns and/or volatilities because it automatically selects the portfolio which offers the overall best risk adjusted performance.

The optimization problem is:

$$\begin{cases} \max\limits_{w} \dfrac{w^{'}(r - r_f e)}{\sqrt{w'\Sigma w}} \quad \text{s.t.} \\ e^{'}w = 1 \end{cases} \tag{3.7}$$

which solved provides the following optimal portfolio weights:

$$w_{MSR} = \frac{\Sigma^{-1}(r - r_f e)}{e'\Sigma^{-1}(r - r_f e)} \tag{3.8}$$

The MSR portfolio can be associated to the tangency portfolio between the Capital Market Line (CML) drawn from the point of risk-free return and the efficient frontier, as it can be seen in Figure 3.2.

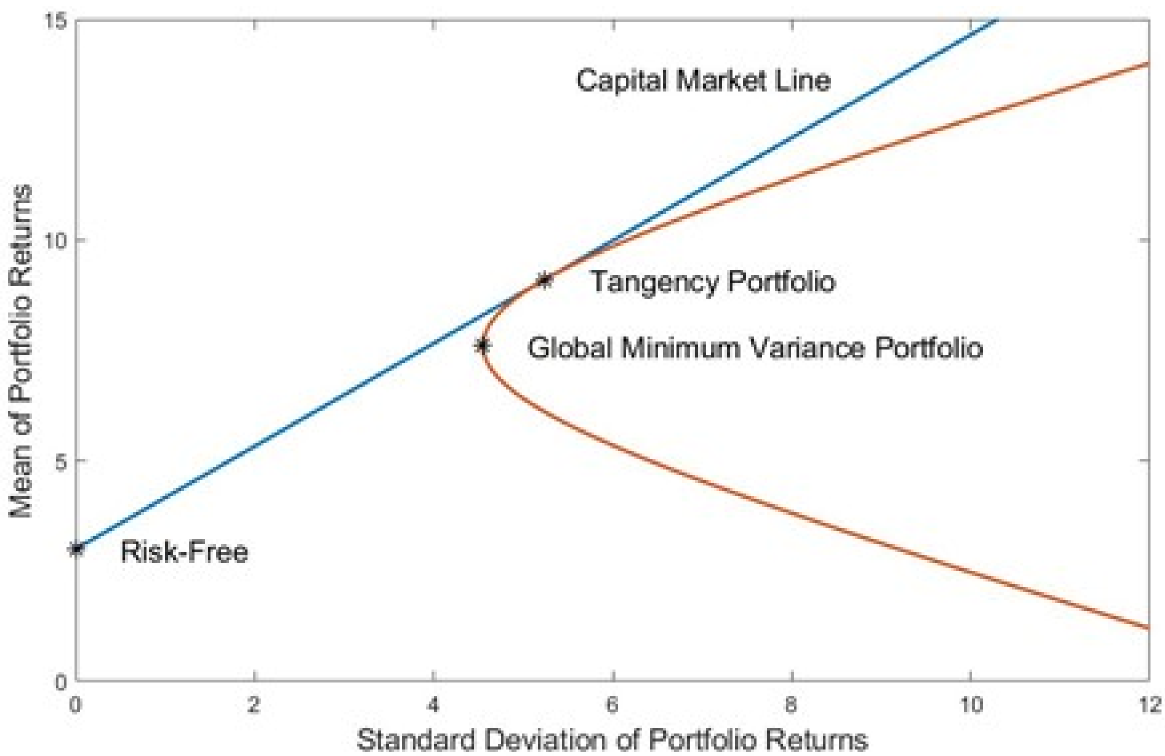

Figure 3.2: GMV and MSR portfolios. *Source: Random simulation generated on Matlab*

3.2 Equally Weighted Portfolio

The next allocation technique is perhaps the most straightforward and easy approach because it does not require the estimation of parameters or to run complex optimization procedures. For this reason, it is useful when limited reliable information about assets characteristics are available. The equally weighted portfolio (EW) simply implies equal capital weights on all the n assets considered:

$$w_{EW} = \frac{1}{n} \tag{3.9}$$

The strategy is broadly used among investors and institutions and it is usually employed when creating benchmark portfolios. The reason is that benefits are not limited to simplicity:

- It mitigates concentration bias. For example, in the classic mean-variance optimization there is an overweighting of assets with extreme returns, low volatility and/or negative correlations among their returns.
- When rebalancing its universe of assets considered, it efficiently performs the so called "Buy low, sell high" strategy by selling expensive assets and buying cheaper ones.
- It captures the size premium by equally weighting small and large companies.
- It always invests in the asset which performs best.
- It requires smaller levels of turnover and, thus, transaction costs, compared to more dynamic asset allocation methods.
- Its out-of-sample performances are relatively good with respect to other allocating strategies (DeMiguel et al. (2009)).

However, the method also presents some drawbacks, mostly due to its simplicity. Because no information concerning assets' characteristics (such as returns, volatilities and correlation matrices) are considered, the strategy provides low diversification benefits.

3.3 Risk Parity Portfolios

As already revealed, alternatives to the MVO have been researched to solve some critical problems about the concentration and estimation bias. One of the most recent and interesting approaches is the risk parity portfolio construction. The concept is to equalize the risk contributions carried by the different elements of the portfolio. Although the topic was already known among CTAs and equity market neutral funds, the first work on the subject was published by Qian (2005), a portfolio manager at Panagora who demonstrated that working with risk contribution can limit the impact of losses of individual components to the overall portfolio. But high approval came in 2008, when Maillard et al. conducted a research on analytical properties of risk parity portfolios (Maillard et al. (2008)).

The reason why it is important to consider risk contributions can be clarified by taking into consideration the traditional 60/40 portfolios example. It has been demonstrated (Qian (2006)) that the risk contribution of the equity part of these portfolios is about 90%, thus far greater than their 60% weight allocation. For this reason, the portfolios appear highly correlated to the stock market and provide weak diversification benefits during financial meltdowns.

The risk contribution of a component i is the share of total portfolio risk attributable to that component. It is obtained multiplying the weight of the asset by its marginal contribution, that is the (positive or negative) change in the overall portfolio risk measure generated by an infinitesimal increment in the weight of the component.

As for the mean-variance case, let us consider a universe of n risky securities, a vector of weights in the portfolio $w = (w_1, ..., w_n)$ and volatility as a risk measure. The variance of the portfolio is:

$$\sigma_p(w) = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{i,j} = \sqrt{w' \Sigma w} \tag{3.10}$$

The marginal contribution can be represented as:

$$\partial_{w_i} \sigma(w) = \frac{\partial \sigma_p(w)}{\partial w_i} = \frac{w_i \sigma_i^2 + \sum_{j \neq i} w_j \sigma_{i,j}}{\sigma_p(w)} = \frac{(\Sigma w)_i}{\sqrt{w' \Sigma w}} \tag{3.11}$$

where $(\Sigma w)_i$ is simply included to provide the vector form equation and represents the i^{th} row of the vector resulting from the product between Σ and w (Maillard et al. (2008)).

The risk contribution of the asset i is:

$$\sigma_i(w) = w_i \partial_{w_i} \sigma(w) \tag{3.12}$$

Intuitively, the overall portfolio risk can be seen as:

$$\sigma_p(w) = \sum_{i=1}^{n} \sigma_i(w) = \frac{w' \Sigma w}{\sqrt{w' \Sigma w}} = \sqrt{w' \Sigma w} \tag{3.13}$$

which is the sum of each of these total contributions.

At this point, two types of risk parity portfolio can be presented: the equally risk contribution portfolio and the inverse volatility one.

3.3.1 Equally Risk Contribution Portfolio

The equally risk contribution portfolio (ERC) is the generic risk parity portfolio designed such that all assets' risk contributions are equal. For reason indicated in the next chapter, all the allocation methods will be performed with restrictions on short-selling and on weights. This implies $w \in [0,1]^n$ and $\sum_{i=1}^{n} w_i = e^{'}w = 1$. The problem becomes:

$$\{w \in [0,1]^n : \sum_{i=1}^{n} w_i = 1,\ w_i \partial_{w_i} \sigma(w) = w_j \partial_{w_j} \sigma(w) \qquad \text{for all } i,j\} \tag{3.14}$$

Given that $\partial_{w_i}\sigma(w)$ is proportional to $(\Sigma w)_i$:

$$\{w \in [0,1]^n : \sum_{i=1}^{n} w_i = 1,\ w_i(\Sigma w)_i = w_j(\Sigma w)_j \qquad \text{for all } i,j\} \tag{3.15}$$

In their research, Maillard, Roncalli and Teiletche proposed to solve the problem using a sequential quadratic programming (SQP) algorithm which minimizes the variance of the risk contribution.

$$w_{ERC} = \min_{w} \left(\sum_{i=1}^{n} \sum_{j=1}^{n} (w_i(\Sigma w)_i - w_j(\Sigma w)_j)^2 \right) \tag{3.16}$$

The existence of the portfolio is ensured when $w_i(\Sigma w)_i = w_j(\Sigma w)_j$ for all i,j, is verified.

3.3.2 Inverse Volatility Portfolio

The inverse volatility portfolio (IV) is a special case of risk parity where all pairwise correlations across assets are assumed to be identical, thus $\rho_{i,j} = \rho$ for all i,j. In this case, the analytical solution to the ERC optimization problem is:

$$w_{IV} = \frac{1/\sigma_i}{\sum_{i=1}^{n} 1/\sigma_i} \tag{3.17}$$

This means that the weight of each asset is the ratio of the inverse of its volatility with the harmonic average of the volatilities. Thus, the assets are inversely weighted to their volatility: the higher the i^{th} volatility the lower its weight in the portfolio.

3.4 Maximum Diversification Portfolio

The last technique is the maximum diversification portfolio (MD), which was proposed by Choueifaty and Coignard (2008). They intended to boost diversification by maximizing the so called 'diversification ratio', which is the ratio of the weighted average of volatilities divided by the total portfolio volatility. In order to do so, the strategy must select assets which minimize/maximize the denominator/numerator (minimize the correlation among the components).

$$\text{DR} = \frac{\sum_{j=1}^{n} w_i \sigma_i}{\sigma_p} = \frac{w^{'}\sigma}{\sqrt{w^{'}\Sigma w}} \tag{3.18}$$

Note that a portfolio which is highly concentrated or with highly correlated holdings may be inadequately diversified and might possess a DR close to 1.

Defined as usual a portfolio of n risky assets whose weights' vector is $w = (w_1, ..., w_n)$, the optimization problem is the following one:

$$\begin{cases} \max\limits_{w} \dfrac{w^{'}\sigma}{\sqrt{w^{'}\Sigma w}} & \text{s.t.} \\ \sum_{i=1} w_i = 1 & \text{and } w_i \in [0, 1] \end{cases} \tag{3.19}$$

By using the Lagrange multiplier (like in the GMV and MSR cases), we obtain the solution:

$$w_{MD} = \frac{\Sigma^{-1}\sigma}{\sigma^{'}\Sigma^{-1}\sigma} \tag{3.20}$$

Chapter 4

Portfolios Construction

In this last chapter I will implement all the approaches previously described to compose multi-factor portfolios diversified through asset classes, risk strategies and asset allocation methods. After an initial brief description of the securities employed, I will provide results of the factor portfolios and then of the levered multi-factor portfolios. To conclude, an analysis of the risk-adjusted performances across different macroeconomic scenarios is explored.

4.1 Data and settings for Backtesting

In order to achieve the objective of building valid diversified long-short portfolios and to take advantage of leverage benefits (e.g. attaining beta-neutral portfolios or setting desired portfolio risk levels), I will make use of the most liquid futures contracts across different asset classes.

Spot, nearest and second-nearest futures prices, spot benchmark prices and P/E ratios are all obtained from Bloomberg while long-term (10 years) bond yields, short-term (3 months) bond yields and PPP conversion rates are obtained from OECD Data. All times series are US Dollar denominated, at a monthly frequency. PPP (Purchasing Power Parity) conversion rates, which are the rates of currency conversion that try to equalize the purchasing power of different currencies, are the only yearly time series. To use these yearly data when computing monthly currencies value measures, the previous year's $(t-1)$ value was employed for each month of year t. For example, to compute value measures for CAD (Canadian Dollar) in January/.../December 2001, the Canada PPP conversion rate in 2000 was used. End date for all the series is December 2019. The analysis aims to examine how the final portfolios performed at least from the start of January 2000 but, because of (12-months) trailing estimations and (one-month delayed) portfolio returns computations, futures and spot price time series date back to September 1995 and all the other times series required to calculate risk measures date back five years earlier. However, recall that not all the securities involved offer reliable extended time series before 2000, so start dates for securities' and measures' time series may vary considerably. The choice to explore portfolios performance starting from (at least) 2000 is motivated by the desire to investigate the profitability of these strategies as more and more conventional investors became aware of them (which, as pointed in the first chapter, occurred in the 2000s) and their response to the several challenging political and economic events occurred in recent years. Examples are the dot-com bubble and the 11th attacks (2000-2002), the 2000s energy crisis (2003-2009), the subprime mortgage crisis and US housing bubble (2007-2009), the European sovereign debt crisis (2009-2019, peaked in 2012), the Chinese stock market crash (2015), the Brexit vote (2016) and other influential events such as environmental disasters and wars. Table A.1 in appendix A provides a summary statistics of nearest to maturity contracts and spot benchmark indices, including their date of inception.

The universe of securities includes 50 assets of different nature. Country equity index futures covers 14 developed and influential equity markets: Australia (S&P/ASX 200), Canada (S&P/TSX 60), Europe (Euro STOXX 50), the US (S&P 500), Japan (Nikkei 255), the UK (FTSE 100), Mexico (S&P/BMV IPC), Switzerland (SMI), Hong Kong (HSI), India (NIFTY 50), Italy (FTSE MIB), Spain (IBEX 35), Germany (DAX 30) and France (CAC 40). For bonds, liquid long-term government bonds futures from 8 developed countries were selected: Australia, Canada, Germany, the US, Japan, the UK, Mexico and Switzerland. The list of currencies tries to emulate the G10 currencies, with the inclusion of Mexico: EUR, GBP, JPY, AUD, NZD, CAD, CHF, NOK, SEK and MXN (as previously stated, all denominated in USD). Finally, a group of the most 18 traded commodities: Crude Oil, Copper, Corn, Gold, Natural Gas, Silver, Soybean, Sugar, Wheat, WTI Crude, Oil, Live Cattle, Lean Hog, Feeder Cattle, Platinum, Cocoa, Cotton, Aluminium and Nickel.

Traditional 60-40 benchmarks are generally constructed allocating 60% of capital to diversified stock indices (for example the S&P500) and 40% capital to safe government bonds (for example 10 years US Notes). Ferri (2010) suggests diversification providing different portfolio compositions which include stock indices of different countries (both developed or emerging markets), government bonds (hedged or unhedged for inflation) of developed and emerging market countries or corporate bonds of different rating, G10 currencies, commodities and alternative assets (such as hedge fund indexes, real estates, derivatives and so on). My benchmark portfolio is a more simplified version of what proposed by Ferri, but still providing a proper grade of diversification. To build the portfolio, I allocated 50% of the capital to a global gross equity index (MSCI World Total Return), 40% to a global aggregate bonds index (Barclays Global Aggregate) and 10% to a diversified commodities composite (S&P Goldman Sachs Commodity Index).

To backtest the strategies, continuous price times series are needed. However, futures prices are instruments that have limited lifespan and need to be rollover to maintain the exposure to their underlying assets. Rollover is basically closing the position from the front month contract to another contract further in the future. If the two contract prices are not equal, the times series would include "jumps" which would condition the general backtested performance. Various techniques allow to adjust this problem smoothing these jumps. The one considered in this thesis is the one which provides better estimates when working with return series. To automatically compose these continuous futures series, I used Bloomberg's GFUT ratio-setting, which composes continuous futures price series through a proportional adjustment approach rolling-over contracts at their first notice.

Securities' and portfolios' weights are rebalanced monthly but, considering the high turnover associated with these dynamic strategies (see Table 4.1) relative to the passive benchmark portfolio, estimated transaction costs must be subtracted from portfolio returns. Locke and Venkatesh (1997) estimated that transaction costs in futures markets range from 0.0004% to 0.033% of the turnover reached. A conservative value of 0.05% (or 5 bps) is applied in this thesis.

Table 4.1: Annualized Turnover rate for Factor Portfolios

The table provides the annualized turnover rate for factor portfolios compared with the one produced by the traditional benchmark portfolio. Series are from 31/10/1996 through 31/12/2019.

	Equities	Bonds	Currencies	Commodities	Benchmark
Value	465.81%	528.38%	75.13%	594.41%	4.30%
Carry	155.36%	548.35%	153.21%	366.78%	4.30%
Momentum	234.76%	253.00%	287.09%	308.47%	4.30%
Volatility	752.42%	652.45%	711.15%	917.22%	4.30%

Finally, the risk-free rate for the computation of excess returns and performance ratios (for example, the Sharpe Ratio) is set equal to 0. This is a simplistic assumption, but if we consider the average US short-term real yield as risk free, we will obtain that for the entire period of the analysis the value is close to zero.

4.2 Factor Portfolios

4.2.1 Value Portfolios

For each asset class, a value portfolio is created using the methodologies explained in chapter 2. In Figure 4.1 cumulative returns of value portfolios and the traditional benchmark are represented covering the period from October 1996 to December 2019.

From the picture, it is clear how the traditional 60/40 benchmark performed better than the value portfolios. In fact, the benchmark produced the greatest cumulative return without manifesting substantial deviation in its path, thus suggesting higher risk-adjusted ratios, such as the Sharpe Ratio. The worst performance was achieved by commodities with a steady decrease lasted almost four years after a previous peak in 2002. Except for currencies, all the style portfolios seem not to be influenced particularly by major market movements, such as the financial crisis in 2008.

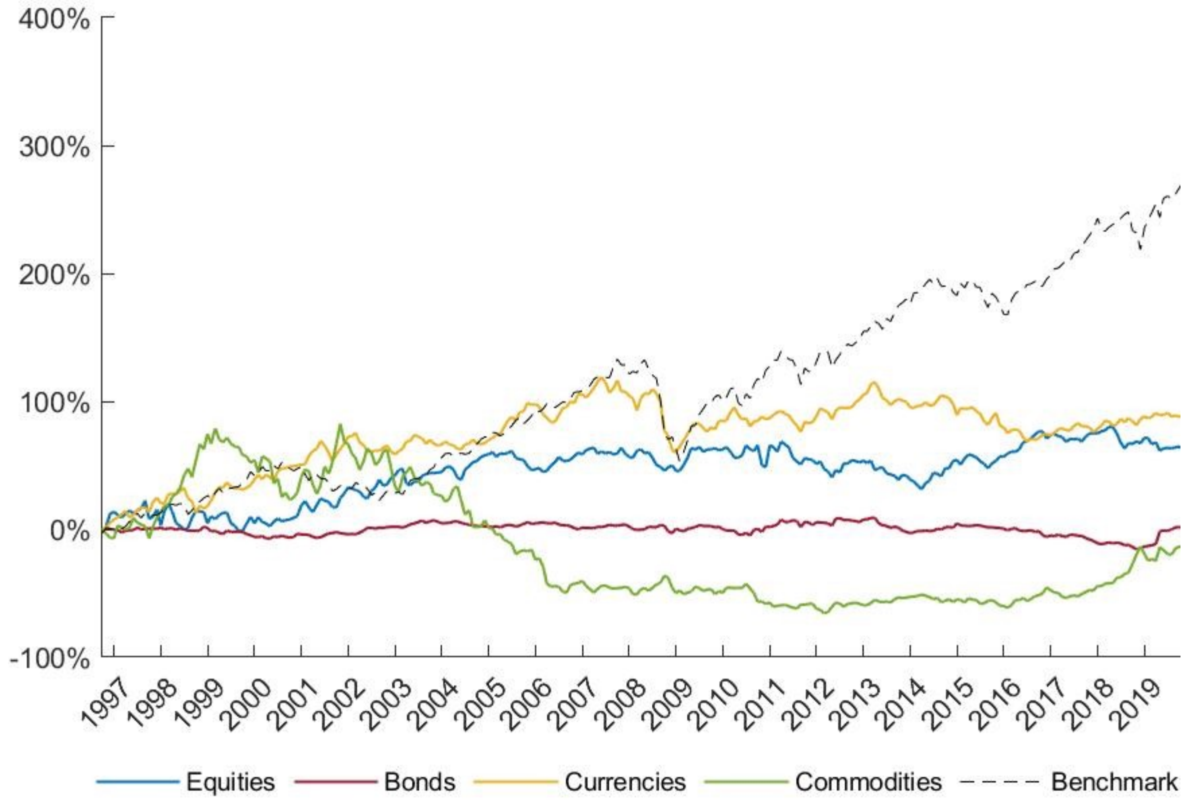

Figure 4.1: Cumulative Returns of Value Portfolios

To better understand the behaviour of the portfolios during the sample period, performance and risk statistics are required. Table 4.2 confirms what Figure 4.1 suggests, that is currencies and global equities were the sole value portfolios which provided positive performances. They respectively realized annualized returns equal to 2.81% and 2.17% and annualized volatility equal to 8.15% and 10.54%, against an annualized returns of 5.91% and annualized volatility of 8.52% achieved by the benchmark. This led the Sharpe Ratio of the benchmark to be more than twofold those of the two style portfolios. An alternative risk-adjusted performance measure is the Sortino Ratio, which considers the downside risk (or semi deviation) of the returns at the denominator to adjust the performance, instead of total portfolio risk. The measures validate what already said about the performances. However, it can be noted increases (with respect to Sharpe ratios) of about 40%-75% for style portfolios against 26% for the benchmark. This indicates that factor portfolios present a higher portion of upside volatility, which is less harmful for investors.

A test for normality is also performed to check if the distributions of the returns are normally distributed. This is important because risk management usually assumes returns to be normally distributed and this underestimates tail behaviour, as mentioned in chapter 1. The Jarque-Bera (JB) test provides the output 1 when the null hypothesis of normality is rejected and 0 otherwise. As we can see, only commodities returns seems to behave as a normal distribution. A confirmation comes also from the analysis of skewness and excess kurtosis, where commodities portfolios exhibits values close to zero, thus acting similarly to a normal distributed curve. Bonds portfolio presents intense positive skewness, indicating a larger portion of extreme positive events with respect to a normal distribution and an excess kurtosis of 11.35, thus with tails far wider than normal. The others two style portfolios, but also the benchmark, seem to behave like anticipated in chapter 1, that is style portfolios have modest negative skewness and fatter tails.

Provided with these measures, adjusted versions of value-at-risk (VaR) and expected shortfall (ES) can be computed. As these original risk measures assume that the asset returns follow a normal distribution, a modified version that takes into consideration skewness and excess kurtosis was considered. The Cornish-Fisher expansion is the expansion which allows to obtain proper VaR and ES to estimate tail features. While the VaR is defined as the loss level that will not be exceeded with a certain confidence level during a certain period of time, the ES represents the expected loss over a specified time period given the loss being greater than the VaR level. Because the ES considers the entire curve shape and satisfied the properties of monotonicity, sub-additivity, homogeneity, and translational invariance, it is considered a more conservative and coherent risk measure than VaR, violates the sub-additivity property (which states that if you add two portfolios together the total risk can't get any worse than adding the two risks separately). Results reflect what the annual standard deviation stated: commodities have the greatest expected shortfall (14.62%), bonds have the lowest value

(6.35%) and benchmark is somewhat positioned similar to the remaining currencies and equities value portfolios at an average value of about 10%. Stated differently, commodities are expected to lose 14.62% when losses overcome the VaR level of 12.51%, whose chance level is 99% over an entire trading month period. These are useful ex-ante measures to estimate future tail events. An alternative measure which measure ex-post risk performances is the maximum drawdown, which provides the measure of the maximum observed loss from a peak to a trough of a portfolio, alternatively quantifying its downside risk. During the period considered, the maximum drawdown was performed by commodities in 30/03/2012, with an 81.16% decrease from its prior peak in 30/11/2001. From a mere max drawdown observation, all the value portfolios (except for commodities) outperformed the benchmark. Nevertheless, by using the Calmar Ratio we can see how the situation is reverse. Calmar Ratio is an alternative performance adjusted measure to Sharpe Ratio and Sortino Ratio, where the portfolio return is adjusted for maximum drawdown. This confirms that value portfolios provided a meager return performance given the downside risk borne.

The final analysis considers results about the annualized alphas and betas (and their t-statistics) generated from the regression of the value portfolios returns on the benchmark returns. Let us begin with alpha, which is a method to compare asset performances relative to a benchmark. All but bonds portfolio exhibit positive annualized alphas and are marginally statistically significant (when the absolute value of their t-statistics is greater than 1.96). This suggests that our market-neutral value portfolios succeeded in identifying overperforming and underperforming assets, generating excessive returns compared to the market, provided the systematic risk borne. Alpha is usually considered when evaluating managers' performance because it a measure that indicates if they achieved returns independent from market movements. Beta measures the systematic risk of a portfolio in comparison to the market as a whole (where the market here is represented by the benchmark portfolio). Beta coefficients for value portfolios are all small and statistically significant, implying that portfolios are not highly exposed to market risk. The valuation of risk by using beta, in this case, massively diverge from the valuation resulted from annualized standard deviation. This may be a sign that a huge portion of non-systematic risk (or idiosyncratic risk) still lies in these portfolios. The Treynor Ratio is another performance ratio which allows to evaluate a return performance considering risk. To do that, it defines the returns per unit of systematic risk. It becomes useless when the numerator is negative, as the other ratios (Sharpe, Sortino and Calmar), but also when the denominator (beta) is negative, as in the case of commodities. As we can see from the results, Treynor Ratios provide a completely different solution than the other risk-adjusted procedures. Considered the low systematic risk carried, equities and currencies portfolios produced an annualized return that was high enough to overperform the benchmark. This clearly confirm what assessed by the estimated alphas. However, because alpha, beta and the Treynor Ratio consider only systematic risk when comparing performances, caution is needed in the presence of portfolios not truly diversified (like these asset class specific factor portfolios which contain a high portion of idiosyncratic risk typical of their asset class).

Table 4.2: Summary Statistics for Value Strategy across Asset Classes

The table provides results about performances and statistics relative to the value portfolios obtained in each asset class compared with the traditional benchmark portfolio. All returns are after transaction costs and series are from 31/10/1996 through 31/12/2019. Some additional information are needed and they will be equal for all the 'Summary Statistics' tables provided afterwards: 1) Performance ratios (Sharpe, Sortino, Calmar and Treynor) are annualized. 2) The Jarque-Bera Test returns a test decision for the null hypothesis that the data comes from a normal distribution with unknown mean and variance. The result is 1 if the test rejects the null hypothesis at the significance level, and 0 otherwise. 3) VaR and ES are adjusted for skewness and excess kurtosis using the Cornish-Fisher expansion. 4) α and β are estimated through linear regression of portfolio returns on the benchmark.

	Equities	Bonds	Currencies	Commodities	Benchmark
Cum. Return	64.87%	0.59%	90.44%	-15.81%	279.79%
Ann. Return	2.17%	0.03%	2.81%	-0.74%	5.91%
Ann. St.Dev.	10.54%	5.20%	8.15%	18.07%	8.52%
Sharpe Ratio	0.21	0.00	0.34	-0.04	0.69
Sortino Ratio	0.30	0.01	0.48	-0.07	0.87
JB Test$_{(99\%)}$	1	1	1	0	1
Skewness	-0.06	1.74	-0.62	-0.06	-0.88
Exc. Kurtosis	2.55	11.35	1.91	0.18	2.76
VaR$_{(99\%)}$	8.79%	3.84%	7.00%	12.51%	7.67%
ES$_{(99\%)}$	11.85%	6.35%	9.07%	14.62%	10.22%
Max Drawdown	22.10%	22.54%	26.83%	81.16%	34.18%
Calmar Ratio	0.10	0.00	0.10	-0.01	0.17
Ann. α	1.68%	-0.59%	0.90%	2.64%	-
t-statistic	2.62	-1.94	1.78	2.41	-
β	0.17	0.12	0.36	-0.29	-
t-statistic	2.28	3.40	6.79	-2.26	-
Treynor Ratio	0.13	0.00	0.08	0.03	0.06

4.3 Carry Portfolios

Figure 4.2 provides the cumulative returns obtained in each asset class through carry methodologies previously described. We can note that currencies carry portfolio resembles its value counterpart with a discrete overall performance and a crash during the 2008 financial crisis. The other asset classes present smoother paths even though equities suffered high downside volatility during the end of the 90s which penalized further its overall negative performance. Commodities carry portfolio seems to provide the best risk-adjusted return over time.

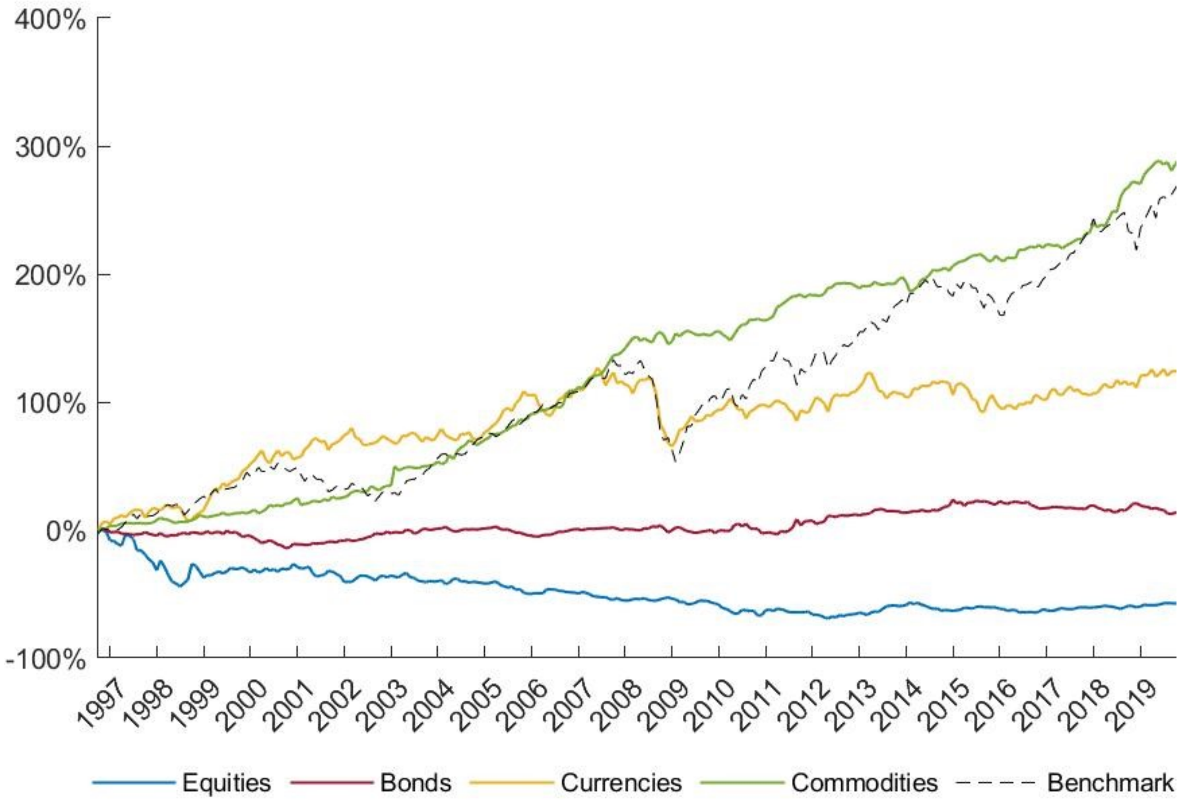

Figure 4.2: Cumulative Returns of Carry Portfolios

In Table 4.3 it is confirmed the superior risk-adjusted performance of commodities, whit a twofold Sharpe Ratio with respect to the passive benchmark. Even considering only the downside risk instead of total risk, rankings are unchanged. However, as for value portfolios, the percentage increase from Sharpe ratio values to Sortino one values leads to think that factor portfolios possess a greater portion of upside volatility and, thus, are relatively less risky than what the Sharpe ratio may suggest. The analysis of the return distributions indicates that none of the portfolios behave like a normal distribution and, except for currencies, reveal positive skewness. Lastly, also carry portfolios confirmed fat tails.

The biggest adjusted ES during extreme negative events are observed in equities (13.03%) and currencies (8.49%). Commodities portfolio reveals a surprisingly high adjusted ES (7.43%), which may be explained by the excess kurtosis correction accomplished with the Cornish-Fisher extension. However, historical analysis of tail events suggests that commodities offered the lowest maximum drawdown and, thus, the best Calmar risk-adjusted performance (1.27) versus a benchmark value of 0.17 and other asset classes' values close to 0.

The t-statistics for alpha are all statistically significant and provided positive results for almost all the portfolios. Equities confirmed its negative performance. Estimated beta are low or negative, even though equities and commodities do not provide significant values (t-statistics equal to 1.42 and 0.62, respectively). Finally, Treynor Ratio suggests that the risk-adjusted performance of the commodities portfolio is 50 times better than that of the benchmark (recall that beta is not significant) and that also currencies offered a superior performance. Again, prudence must be exercised when considering this ratios because the portfolios may still include a great portion of idiosyncratic risk.

Table 4.3: Summary Statistics for Carry Strategy across Asset Classes

The table provides results about performances and statistics relative to the carry portfolios obtained in each asset class compared with the traditional benchmark portfolio. All returns are after transaction costs and series are from 31/10/1996 through 31/12/2019. For additional information about the statistics provided, please refer to Table 4.2

	Equities	Bonds	Currencies	Commodities	Benchmark
Cum. Return	-56.61%	15.34%	127.85%	290.48%	279.79%
Ann. Return	-3.53%	0.62%	3.61%	6.03%	5.91%
Ann. St.Dev.	11.84%	4.79%	8.03%	4.60%	8.52%
Sharpe Ratio	-0.30	0.13	0.45	1.31	0.69
Sortino Ratio	-0.47	0.21	0.63	2.40	0.87
JB Test$_{(99\%)}$	1	1	1	1	1
Skewness	0.80	0.32	-0.62	1.94	-0.88
Exc. Kurtosis	4.82	1.82	1.59	16.45	2.76
VaR$_{(99\%)}$	9.23%	3.37%	6.65%	3.91%	7.67%
ES$_{(99\%)}$	13.03%	4.30%	8.49%	7.43%	10.22%
Max Drawdown	69.14%	14.95%	27.19%	4.57%	34.18%
Calmar Ratio	-0.05	0.04	0.13	1.32	0.17
Ann. α	-3.62%	1.99%	1.14%	5.85%	-
t-statistic	-5.01	7.27	2.64	20.79	-

Continued on next page

	Equities	Bonds	Currencies	Commodities	Benchmark
β	0.12	-0.21	0.45	0.02	-
t-statistic	1.42	-6.53	8.94	0.62	-
Treynor Ratio	-0.30	-0.03	0.08	3.00	0.06

4.4 Momentum Portfolios

Cumulative returns for momentum portfolios are presented in Figure 4.3. Overall, the performances of the four asset classes have been all positive with bonds being nearly profitable and equities providing a final return similar to the benchmark, overcoming it by more than 400% in the middle of the financial crisis and crashing subsequently.

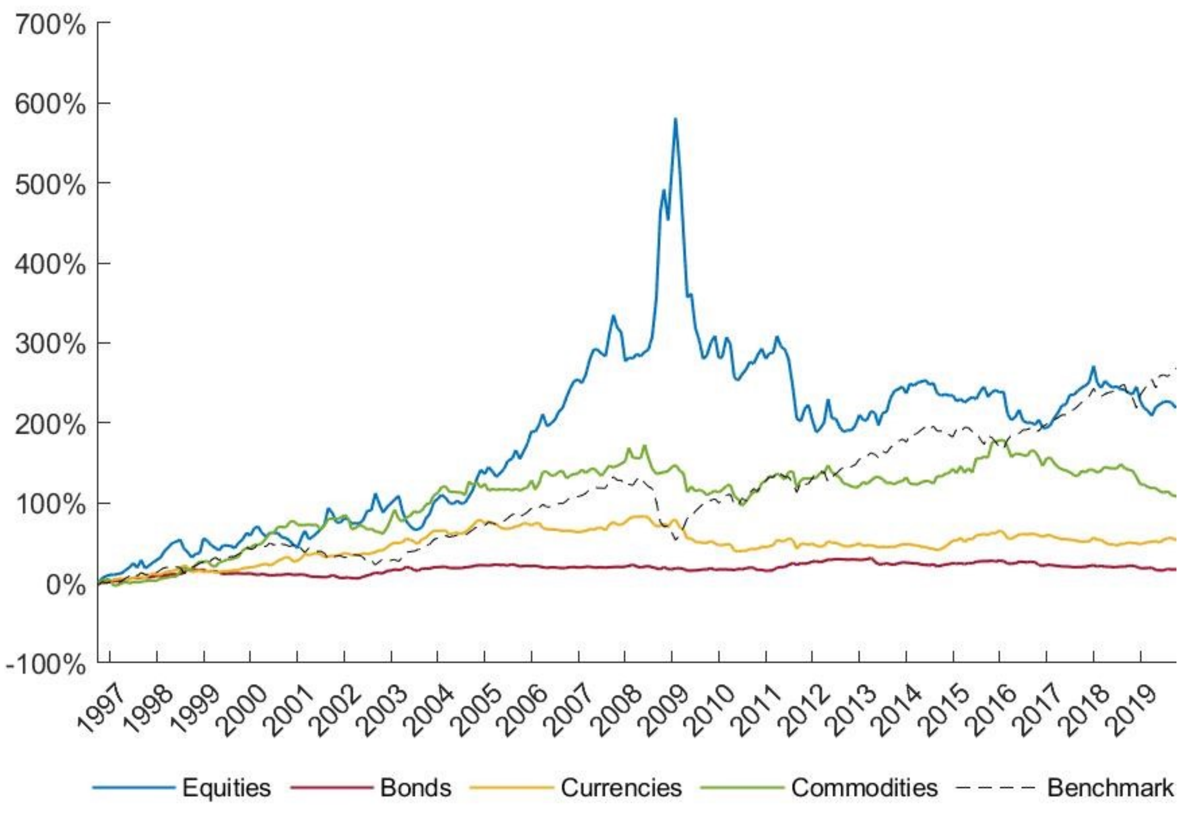

Figure 4.3: Cumulative Returns of Momentum Portfolios

The positivity of the performances is verified in Table 4.4. Each asset class provided annualized returns ranging from 0.65% to 5.32%, approaching the annualized performance of the benchmark equal to 5.91%. However, due to higher annualized volatility, the risk-adjusted performances remain lower. Again, the presence of a higher degree of upside volatility skew the results, validated by the percentage increase from Sharpe Ratios to Sortino Ratios. However, benchmark still overperformed asset class specific momentum portfolios.

Reinforced by negative skew distributions and fat tails, Jarque-Bera tests once again did not unveiled normality similarities in return distributions.

Not surprisingly, equities momentum portfolio registered the highest maximum drawdown (57.69%) during the post financial crisis period, followed by the benchmark (34.18%) and then commodities and currencies (about 28%). Calmar Ratio confirmed the Sharpe Ratio rankings indicating the benchmark as the best performer relative to the specific risk borne (maximum drawdown), followed by slightly different ranking performances for equities, commodities and currencies. Bonds, whose total volatility was quite low, presented a discrete level of maximum drawdown which further penalized its risk-adjusted performance.

Finally, statistically significant alpha measures indicates that the momentum portfolios produced excess returns with respect to the benchmark, considered their systematic risk. This cannot be verified by Treynor Ratios as mostly estimated beta present negative exposure to the market or not statistically significant values.

Table 4.4: Summary Statistics for Momentum Strategy across Asset Classes

The table provides results about performances and statistics relative to the momentum portfolios obtained in each asset class compared with the traditional benchmark portfolio. All returns are after transaction costs and series are from 31/10/1996 through 31/12/2019. For additional information about the statistics provided, please refer to Table 4.1

	Equities	Bonds	Currencies	Commodities	Benchmark
Cum. Return	233.59%	16.37%	51.62%	109.55%	279.79%
Ann. Return	5.32%	0.65%	1.81%	3.23%	5.91%
Ann. St.Dev.	15.15%	3.56%	6.14%	9.37%	8.52%
Sharpe Ratio	0.35	0.18	0.29	0.34	0.69
Sortino Ratio	0.51	0.26	0.38	0.49	0.87
JB Test$_{(99\%)}$	1	1	1	1	1
Skewness	0.24	-0.21	-0.57	-0.20	-0.87
Exc. Kurtosis	3.30	1.18	2.11	1.33	2.76

Continued on next page

	Equities	Bonds	Currencies	Commodities	Benchmark
$\text{VaR}_{(99\%)}$	12.18%	2.75%	5.36%	7.19%	7.67%
$\text{ES}_{(99\%)}$	16.97%	3.46%	7.02%	9.15%	10.22%
Max Drawdown	57.69%	12.07%	23.85%	28.05%	34.18%
Calmar Ratio	0.09	0.05	0.08	0.12	0.17
Ann. α	8.35%	0.70%	2.21%	3.73%	-
t-statistic	9.15	3.22	5.90	6.49	-
β	-0.33	0.00	-0.04	-0.02	-
t-statistic	-3.14	0.09	-0.89	-0.25	-
Treynor Ratio	-0.16	2.94	-0.47	-1.92	0.06

4.5 Volatility Portfolios

The last style premia to discuss is volatility (or low beta strategy). In Figure 4.4 we can note that except for equities (and marginally bonds), none of the asset class beat the benchmark. Moreover, both equities and commodities seemed to suffer the 2008 financial crisis whilst currencies dropped in late 2012, perhaps conditioned by the worsening of the European sovereign debt crisis occurred in that period.

As usual, Table 4.5 provides summary statistic for the volatility strategy across asset classes. The only asset class which presented a negative cumulated return over the period is commodities, also penalized by the highest annualized volatility seen so far across strategies. This should not surprise as this strategy makes use of leverage to set beta-neutral portfolios, though constrained to a 200% amount. Overall, asset classes are in line with their value, carry and momentum equivalents, providing low or discrete risk-adjusted performance (both for total and downside risk) which did not overcome the benchmark (except for commodities carry portfolio, which acted handsomely over the period considered). As for value strategy, commodities presented returns distribution which resembles a normal distribution while other asset classes revealed fatter tails and left-skewed characteristics.

Adjusted VaR and adjusted ES reflect roughly the total risk of each portfolio, by displaying extreme expected losses in commodities and equities. Adjusted ES is relatively higher for the passive portfolio than for currencies given almost the same amount of total risk. This may be cause by a larger presence of extreme returns, confirmed by skewness and excess kurtosis. However, this is not emulated by maximum drawdown results. In fact, currencies presented the second highest maximum drawdown surmounting both benchmark and equities. Calmar Ratio does not provide crucial additional information to the previous risk-adjusted ratio.

The analysis of alphas and betas does not offer positive suggestions. Except for bonds portfolio, which produced a positive significant annualized alpha, for the other asset classes the value is not statistically significant. Betas analysis is not encouraging too. The estimations are nearly significant for currencies and commodities and suggested a market exposure way higher than preferred. In fact, despite portfolios were constructed to be market neutral, beta estimated are not closer to zero than the other strategies. Furthermore, estimated beta for equities portfolio is equal to 0.86. However, it must be recalled that each portfolio has been constructed to be market neutral with respect to asset specific risk-weighted indexes and not to the benchmark. Treynor Ratio confirmed the poor performances already largely discussed.

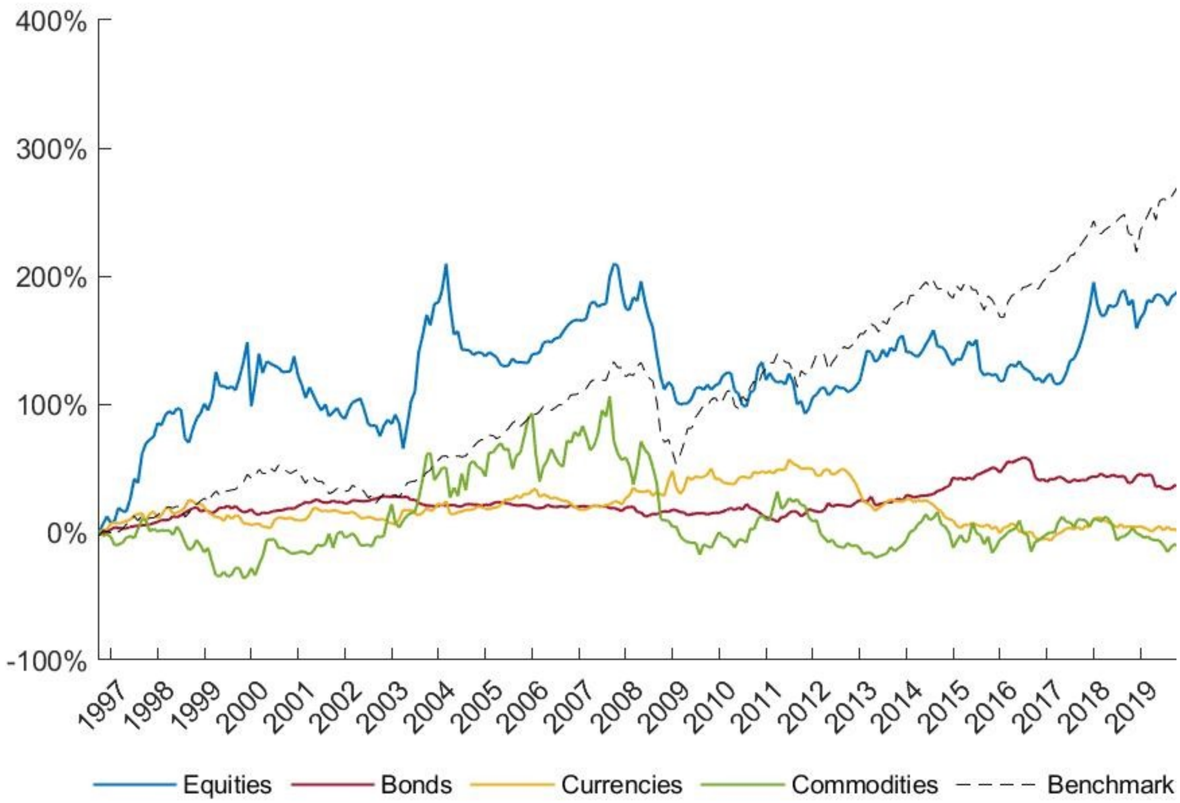

Figure 4.4: Cumulative Returns of Volatility Portfolios

Table 4.5: Summary Statistics for Volatility Strategy across Asset Classes

The table provides results about performances and statistics relative to the volatility portfolios obtained in each asset class compared with the traditional benchmark portfolio. All returns are after transaction costs and series are from 31/10/1996 through 31/12/2019. For additional information about the statistics provided, please refer to Table 4.2

	Equities	Bonds	Currencies	Commodities	Benchmark
Cum. Return	192.97%	37.28%	0.82%	-12.09%	279.79%
Ann. Return	4.73%	1.37%	0.04%	-0.55%	5.91%
Ann. St.Dev.	14.51%	5.25%	8.54%	21.68%	8.52%
Sharpe Ratio	0.33	0.26	0.00	-0.03	0.69
Sortino Ratio	0.46	0.34	0.01	-0.04	0.87
JB Test$_{(99\%)}$	1	1	1	0	1
Skewness	-0.14	-0.72	0.14	-0.11	-0.88
Exc. Kurtosis	3.03	3.90	1.29	0.44	2.76
VaR$_{(99\%)}$	12.62%	5.29%	6.18%	15.53%	7.67%
ES$_{(99\%)}$	17.43%	7.37%	7.72%	18.53%	10.22%
Max Drawdown	37.91%	15.75%	40.59%	61.19%	34.18%
Calmar Ratio	0.12	0.09	0.00	-0.01	0.17
Ann. α	0.41%	2.05%	-0.31%	0.19%	-
t-statistic	0.53	6.44	-0.60	0.14	-
β	0.86	-0.09	0.12	0.26	-
t-statistic	9.77	-2.44	1.94	1.74	-
Treynor Ratio	0.05	-0.15	0.00	-0.02	0.06

Overall, the four strategies across individual asset classes (except the commodities carry portfolio) provided poor performances with respect to the benchmark, providing low or negative annualized returns after costs and, for equities and commodities, large annualized standard deviation. This lowered the absolute and adjusted performances for both total and downside risks. Furthermore, it has been confirmed the non-normality assumption of the return distributions with typical left-skewed distributions and fat tails for the majority of the portfolios observed. The analysis of the regression of each portfolio against the benchmark revealed contrarian situations alternating positive and negative performances. However, lots of the coefficients were not statistically significant and portfolios may still contain a great degree of idiosyncratic risk which must be diversified away.

To do so, global factor portfolios were composed following the procedure described in chapter 2, that is by using an equal-volatility scheme. It will be shown in the next section that creating these factor portfolios, diversified across asset classes, does improve considerably overall performances. This was augmented by the low correlation among each portfolio return, which allowed to reach a superior diversification effect. As we can see in Table 4.6, correlations across asset class specific portfolios are extremely low (about 0.02) and momentum is the strategy which generally produced the highest rate of correlation (even though the absolute highest correlation was obtained between returns of currencies in value and carry strategies, 0.79). Compared to the benchmark and a pure global equity index (MSCI World), the average correlation is equal to 0.07, with the highest ratio obtained among returns of the volatility equities portfolio and the benchmark.

Table 4.6: Correlation Matrix for Factor Portfolios among Asset Classes

The table shows the correlations for returns produced among each factor portfolio among each asset classes (equities (EQ), bonds (BO), currencies (CU) and commodities (CO)), traditional equity beta (MSCI World Index (MW)) and the traditional benchmark (BM). All returns are considered after transaction costs and series are from 31/10/1996 through 31/12/2019.

		Value				Carry				Momentum				Volatility					
		EQ	BO	CU	CO	EQ	BO	CU	CO	EQ	BO	CU	CO	EQ	BO	CU	CO	MW	BM
Value	EQ	1.00	-0.02	0.11	-0.10	0.21	-0.08	0.13	0.07	-0.05	0.02	-0.03	0.01	0.05	-0.10	0.10	0.04	0.13	0.14
	BO		1.00	0.10	0.07	-0.00	-0.23	0.12	0.05	0.06	0.00	0.10	0.06	0.12	-0.25	0.03	0.02	0.18	0.20
	CU			1.00	0.07	-0.29	-0.29	0.79	0.02	-0.04	-0.09	0.11	-0.09	0.13	-0.11	-0.03	0.10	0.38	0.38
	CO				1.00	0.04	0.09	0.04	-0.06	0.06	-0.02	-0.01	-0.38	-0.10	0.01	-0.06	-0.00	-0.07	-0.13
Carry	EQ					1.00	-0.01	-0.21	-0.05	-0.11	-0.05	-0.11	0.01	-0.13	-0.03	0.00	-0.05	0.10	0.09
	BO						1.00	-0.31	0.09	0.02	0.11	-0.08	0.02	-0.06	0.26	-0.07	-0.01	-0.36	-0.37
	CU							1.00	-0.02	-0.07	-0.05	0.08	-0.08	0.21	-0.18	-0.10	0.12	0.48	0.47
	CO								1.00	0.02	0.12	0.02	0.11	0.04	-0.03	-0.01	-0.12	-0.01	0.04
Momentum	EQ									1.00	0.13	0.39	0.25	0.08	0.02	-0.03	-0.02	-0.17	-0.19
	BO										1.00	0.46	0.17	0.03	0.23	0.08	-0.07	-0.08	0.01
	CU											1.00	0.39	0.03	0.05	0.05	0.05	-0.07	-0.05
	CO												1.00	0.12	0.05	-0.11	0.03	-0.04	-0.02
Volatility	EQ													1.00	-0.15	0.04	0.07	0.49	0.51
	BO														1.00	0.08	-0.14	-0.15	-0.15
	CU															1.00	0.05	0.11	0.12
	CO																1.00	0.09	0.10
	MW																	1.00	0.96
	BM																		1.00

4.5.1 Global Factor Portfolios

For each strategy, a global factor portfolio is created applying an equal-volatility weighting scheme on the four asset class specific portfolios. using the methodologies explained in chapter 2. Figure 4.5 provides the cumulative returns of global factor portfolios from November 1997 to December 2019. It can be noted a clear improvement in performances, which are generally less volatile and not strongly conditioned by economic and financial crisis occurred during the sample period.

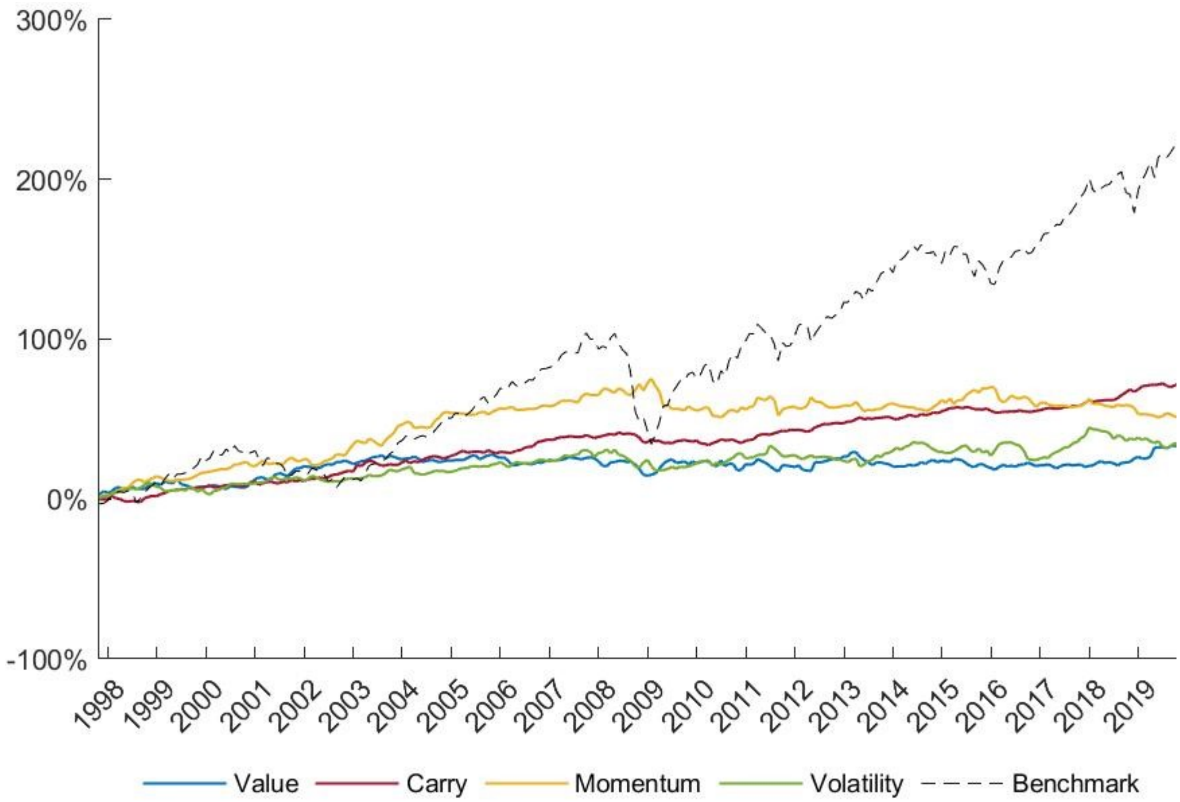

Figure 4.5: Cumulative Returns of Global Factor Portfolios

Table 4.7 helps us to quantify the degree of performances. Cumulative and annualized returns for factor portfolios ranged (respectively) from 33.59% to 73.78% and 1.32% to 2.52%, while the benchmark kept overperforming with values equal to 232.61% and 5.57%. However, the diversification obtained by low correlations among asset classes and the greater amount of capital allocated to less risky assets allowed to lower considerably the total risk. Except for carry, which obtained an annualized volatility equal to 1.90% clearly benefitting from the superior commodities performance, the other style premia produced an annualized standard deviation close to 4.5% against a benchmark volatility of 8.5%. This permitted Sharpe ratios to get closer to the reference level achieved by the benchmark, that is a Sharpe Ratio of 0.65. Carry, whose risk-adjusted performance is equal to 1.00, acted greatly also limiting the analysis to downside risk doubling the performance and suggesting that a substantial portion of its risk is "not harmful". Tests on normality did not discover normal similarities. However, if we look at skewness and excess kurtosis, we can note how they do not depart significantly from standard normal values equal to 0.

The biggest improvements appeared when estimating ex-ante and ex-post risk exposure. In fact, both adjusted VaR, adjusted ES and maximum drawdown plummeted with respect to the benchmark. However, a deeper look at the drawdown chart (not provided for factor portfolios but noticeable in the chart offered in the next section for the levered multi-factor portfolios) advises that while the benchmark suffered two major drawdowns during the dot-com bubble and the subprime crises, the risk premia strategies registered frequently major and minor drawdown during the entire second decade of 2000. The Calmar Ratio indicates that all the portfolios performed equally with respect to the maximum drawdown shouldered, except for carry, which overperformed against the others.

Annualized alphas are all statistically significant and suggest weak overperformance with respect to the benchmark. Beta coefficients, which resulted nearly statistically significant for carry and momentum and highly statistically significant for value and volatility, indicate low or negative exposures to market risk. Finally, the Treynor Ratio awarded style portfolios with respect to the benchmark. The difference between Sharpe ratios and Treynor ratios when ranking the performances once again may indicate that a significant level of idiosyncratic risk is still included in global factor portfolios.

Table 4.7: Summary Statistics for the Global Factor Portfolios

The table provides results about performances and statistics relative to the global factor portfolios obtained through equal-volatility weighting in each asset class compared with the traditional benchmark portfolio. All returns are after transaction costs and series are from 28/11/1997 through 31/12/2019. For additional information about the statistics provided, please refer to Table 4.2

	Value	Carry	Momentum	Volatility	Benchmark
Cum. Return	33.59%	73.78%	51.70%	34.44%	232.61%
Ann. Return	1.32%	2.52%	1.90%	1.34%	5.57%
Ann. St.Dev.	4.18%	2.53%	4.54%	4.49%	8.52%
Sharpe Ratio	0.31	1.00	0.42	0.30	0.65
Sortino Ratio	0.55	1.74	0.54	0.42	0.81
JB Test$_{(99\%)}$	1	1	1	1	1
Skewness	0.39	0.26	-0.70	-0.37	-0.91

Continued on next page

	Value	Carry	Momentum	Volatility	Benchmark
Exc. Kurtosis	1.25	1.70	2.89	0.80	2.91
$VaR_{(99\%)}$	2.63%	1.62%	4.20%	3.43%	7.79%
$ES_{(99\%)}$	3.23%	2.11%	5.67%	4.21%	10.41%
Max Drawdown	10.33%	5.63%	13.93%	10.16%	34.18%
Calmar Ratio	0.13	0.45	0.14	0.13	0.16
Ann. α	0.68%	2.34%	2.33%	0.63%	-
t-statistic	2.68	14.86	8.27	2.33	-
β	0.12	0.03	-0.06	0.14	-
t-statistic	4.23	1.77	-1.85	4.47	-
Treynor Ratio	0.11	0.79	-0.31	0.10	0.06

Before proceeding with the next section, a brief analysis of the correlation matrix for the global factor portfolios returns is included (Table 4.8). As for individual asset class specific portfolios, general correlation among strategies is close to zero or even negative, implying that also naïve diversification approaches may improve further overall portfolio performances. Furthermore, it can be seen that also correlation among strategies and market benchmarks are truly low, that is diversification would be obtained also by simply blending factor strategies with passive portfolios.

Table 4.8: Correlation Matrix for the Global Factor Portfolios

The table shows the correlations for returns produced among each global factor portfolio, traditional equity beta (MSCI World Index (MSCI)) and the traditional benchmark. All returns are considered after transaction costs and series are from 28/11/1997 through 31/12/2019.

	Value	Carry	Momentum	Volatility	MSCI	Benchmark
Value	1	0.16	-0.09	-0.09	0.27	0.25
Carry		1	0.03	-0.06	0.10	0.11
Momentum			1	0.11	-0.14	-0.11
Volatility				1	0.25	0.26
MSCI					1	0.96
Benchmark						1

4.6 Multi-Factor Portfolio

In this section, I will present results about the multi-factor portfolios composed by blending together the four global factor portfolios by making use of the six different asset allocation methods described in chapter 3 and I will also target annualized portfolio volatility to 8% through leverage, limiting leverage factors to 1000%. This allows to obtain superior returns while limiting the increase of risk to suffer. However, as volatility risk premia already embedded leverage, the total scaling effect for some portfolios will occasionally exceed that level. The choice of target volatility was done considering the historical benchmark annualized volatility obtained from 1990 to 2000. With the gift of hindsight, this is a reliable measure as the realized benchmark annualized volatility during our sample period was not different (8.53%). Unlevered portfolios performances are presented in Appendix B.

Before proceeding, it is important to inform that lower and upper bounds for individual strategies' participation were set to be respectively equal to 10% and 50%. By doing so, I eased the problem of letting some assets concentrate for more than a half of portfolio's total position (discussed in chapter 3) while also denying the possibility of setting asset's weights close to zero, thus cutting diversification benefits. This procedure was applied to GMV, MSR, ERC and MD optimization problems. Furthermore, to be consistent with the positive weight constraints imposed (by construction) in the equally weighted portfolio, all the asset allocation strategies were considered long-only.

Let us start with the cumulative returns plot in Figure 4.6 which covers a period of twenty years: January 2000 to December 2019. Thanks to leverage effect, cumulative returns generated by all the asset allocation methods now exceed the benchmark. During the period, two events conditioned particularly the overall performance and boosted instability: the 2008 financial crisis and the 2015-2016 stock market sell-off. This last occurrence can also be seen as the moment when performances started to diverge the most, except for MSR and EW which started their variation in 2009.

Table 4.9 provides all the summary statistics needed to evaluate portfolios profitability and riskiness. In general, portfolios which favour a better management of volatility like the GMV and the risk parity strategies, provided the best performances both in absolute terms and relative to the risk associated (total risk for Sharpe Ratio or downside risk for Sortino Ratio). Annualized portfolios volatility did not accomplish completely the 8% target set, presumably because of the presence of transaction costs and leverage constraints. Assumptions of normality were all rejected and returns distribution displayed mostly a slightly positive skewness, thus the presence of more extreme positive events than normal and fat tails, which has been a common characteristic observed in all the previous portfolios.

Estimated and examined “tail” risks, despite the great level of leverage embedded, were all in line or lower than the benchmark, with volatility-optimizer strategies achieving their task of providing the safest portfolios. In fact, GMV, ERC and IV forecasted monthly average losses during the worst 1% of months’ days equal to about 8.6% and an observed maximum drawdown of 25% against benchmarks values of 10.69% and 34.18%, respectively (Figure 4.7 provides the drawdown function for the portfolios). Return performances adjusted for maximum drawdown do not include additional information: GMV keeps overperforming, followed by the other strategies which try to minimize or optimize risk.

Linear regression on the benchmark revealed the generation of superior statistically significant alphas and statistically significant beta values which suggest that levered portfolios are one fifth less risky than the market. The exception is the MSR portfolio with an estimated beta of 0.07, but not statistically significant (t-statistics equal to 0.99). Finally, the Treynor Ratio confirmed the overperformance of these levered portfolios diversified by asset class and style premia.

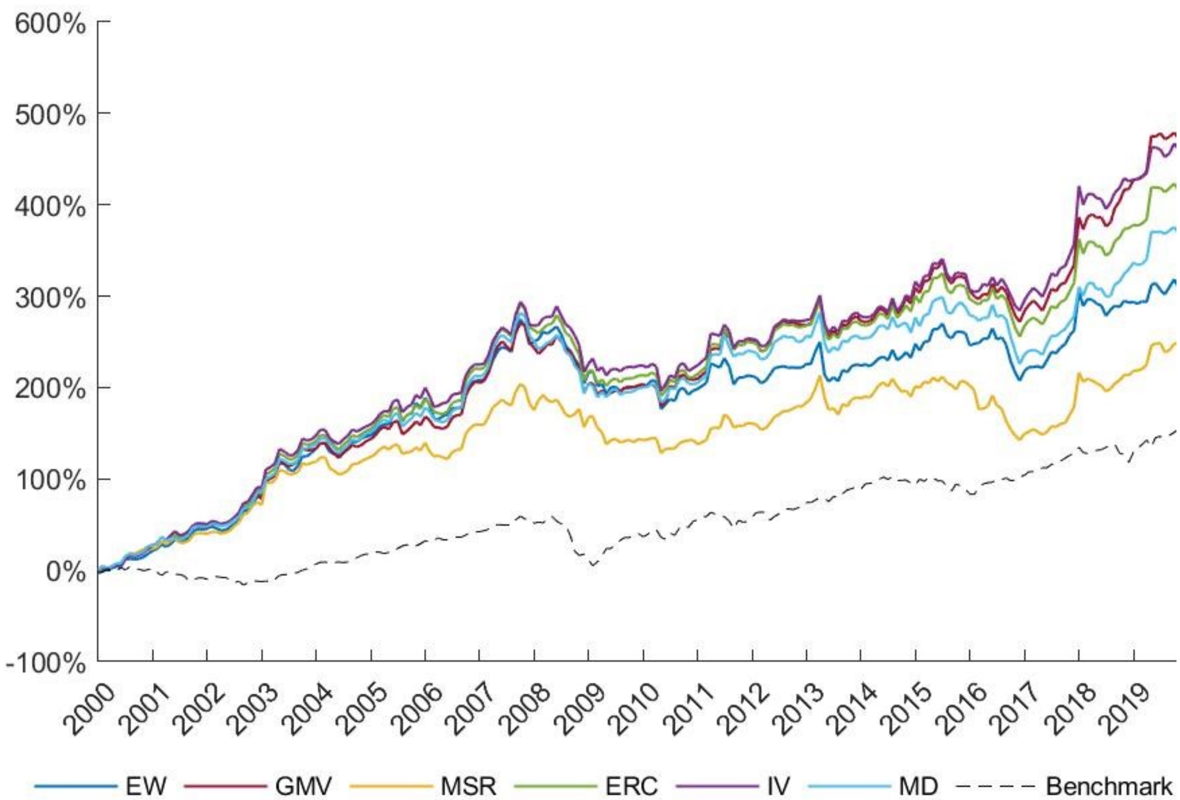

Figure 4.6: Cumulative Returns of Levered Multi-Factor Portfolios

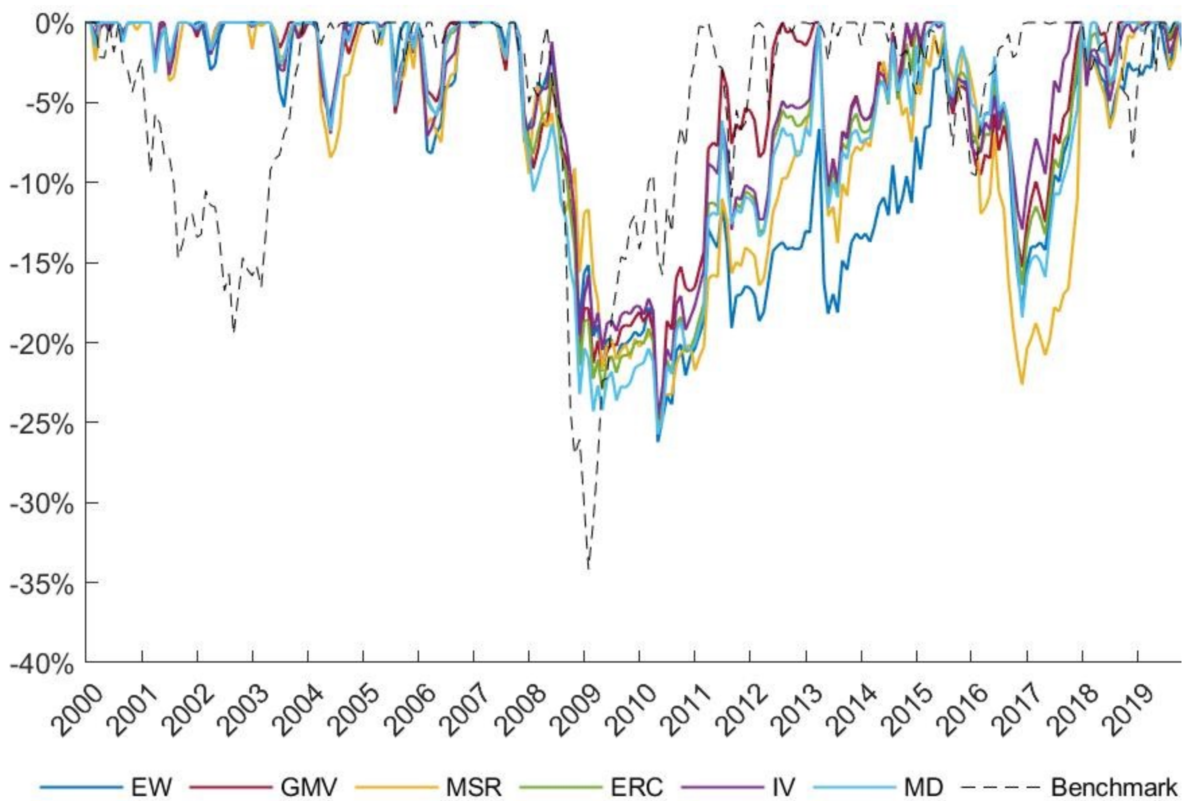

Figure 4.7: Drawdowns of Levered Multi-Factor Portfolios

Table 4.9: Summary Statistics for the Levered Multi-Factor Portfolios

The table provides results about performances and statistics relative to the multi-factor portfolios obtained through six different asset allocation strategies and scaled to obtain an annual standard deviation equal to 10%, compared with the traditional benchmark portfolio. All returns are after transaction costs and series are from 31/01/2000 through 31/12/2019. For additional information about the statistics provided, please refer to Table 4.2

	EW	GMV	MSR	ERC	IV	MD	Benchmark
Cum. Return	327.08%	493.83%	262.07%	437.58%	489.57%	386.02%	159.78%
Ann. Return	7.53%	9.32%	6.64%	8.77%	9.28%	8.23%	4.89%
Ann. St.Dev.	9.52%	9.33%	9.72%	9.40%	9.50%	9.32%	8.53%
Sharpe Ratio	0.79	1.00	0.68	0.93	0.98	0.88	0.57
Sortino Ratio	1.10	1.71	1.08	1.46	1.51	1.37	0.71
JB Test$_{(99\%)}$	1	1	1	1	1	1	1
Skewness	-0.09	0.40	0.57	0.20	0.31	0.08	-0.88
Exc. Kurtosis	2.56	2.11	3.87	2.03	3.13	1.23	3.08
VaR$_{(99\%)}$	7.57%	5.87%	6.96%	6.43%	6.87%	6.18%	7.94%

Continued on next page

	EW	GMV	MSR	ERC	IV	MD	Benchmark
$ES_{(99\%)}$	10.37%	7.77%	9.89%	8.56%	9.65%	7.88%	10.69%
Max Drawdown	26.22%	24.55%	24.98%	25.75%	24.82%	25.74%	34.18%
Calmar Ratio	0.29	0.38	0.27	0.34	0.37	0.32	0.14
Ann. α	6.55%	8.36%	6.54%	7.84%	8.23%	7.41%	-
t-statistic	10.70	13.87	10.26	12.92	13.45	12.28	-
β	0.23	0.20	0.07	0.20	0.22	0.19	-
t-statistic	3.25	2.79	0.99	2.85	3.08	2.66	-
Treynor Ratio	0.33	0.48	0.91	0.44	0.43	0.44	0.05

Overall, additional diversification obtained through multiple blending steps finally provided highly profitable portfolios capable of mimic or overperform the benchmark risk-adjusted performance, even after having considered the high amount of transaction costs and the added riskiness provided by leverage. This was particularly true when considering asset allocation methods which favour low volatility levels, such as GMV, ERC and IV. Given the minimal performance differences between them, but the clear different ease of implementation, IV can be considered the best allocation strategy for the period, securities and risk premia considered.

Recalling what already said in chapter 2, that is different global factor portfolios were generated considering asset allocation strategies other than the sole equal-volatility weighting scheme, other 30 levered multi-factor portfolios were composed using the usual six allocation methods and analysed. Sharpe Ratios obtained from these portfolios, combined using strategies different from that suggested in literature, are displayed in Appendix C.

4.7 Macroeconomic Sensitivities

Ilmanen et al. (2014) presented an interesting alternative risk analysis which allows to comprehend how these portfolios responded to different macroeconomic scenarios, thus providing insights of when it is more favourable to adopt these strategies and when it is better loosen their usage. In their research, they provided a guideline to verify the sensitivity of investable return sources (as our portfolios) to non-investable macro factors. According to their procedure, some of the most influential macroeconomic indicators were first taken into consideration: growth, inflation, real interest rates and volatility. Long and reliable times series for some global macro variables were not found, so that US indicators were used, given their historical dominant role in the global economy:

- For growth, the US PMI (Purchasing Managers Index) was retrieved from Quandl.

- For inflation, the y-o-y change in the US CPI (Consumer Price Index) was obtained from OECD Data.

- For real interest rates, the average yield between long-term (10 years) US real interest rates and short-term (2 years) US real interest rates (based on their respective nominal yield adjusted for US CPI inflation rate) were obtained on Bloomberg.

- For volatility, the CBOE VIX (Volatility Index) was acquired from Bloomberg.

Historical median values were computed for each indicator using a rolling period of 10 years (or 120 months, as data is monthly) and recession months were identified as the periods when the macroeconomic variable was lower than its historical median. Macroeconomic indicators and recession shadows are provided in Figure 4.8.

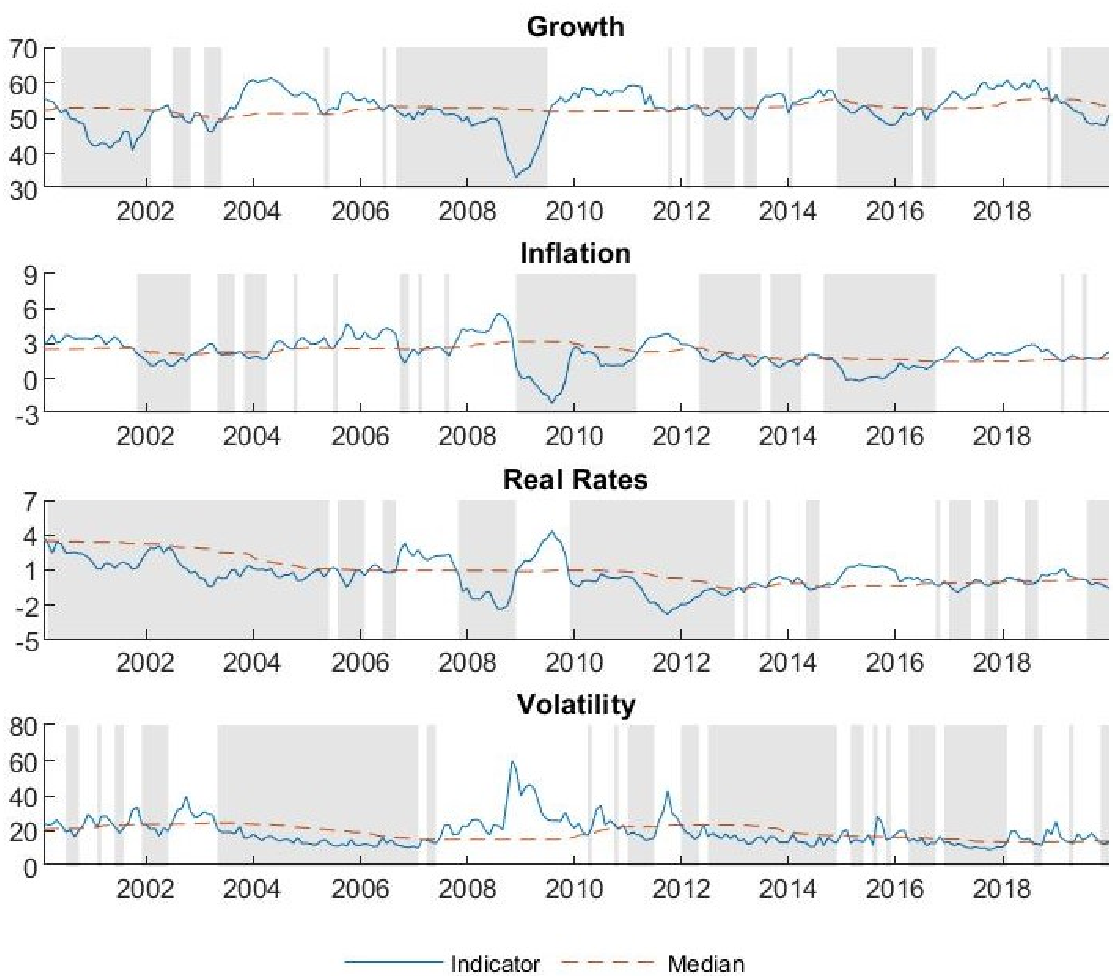

Figure 4.8: Macroeconomic Indicators

Once recession periods were available, Sharpe Ratios for each levered multi-factor portfolio were recomputed to verify the adjusted-performance during these "up" and "down" environments. For instance, to compute the performance of a portfolio during unusually decreasing growth, it was sufficient to set original $r_{p,t} = 0$ whenever the median value was lower than the growth indicator (that is in presence of unusually increasing growth). Figure 4.9 shows Sharpe Ratio levels achieved by portfolios in each macroeconomic scenario.

In general, findings are that levered portfolios diversified across asset classes and return premia appear less sensitive to macroeconomic risks while the traditional benchmark, which is diversified solely across asset classes, demonstrates more variable Sharpe Ratios. Multi-factor portfolios performed slightly better during periods of stagnant growth, even though the difference with economic booms is not so evident. They also favoured periods of increasing inflation, low real interest rates and decreasing volatility. While the latter characteristic is quite common among assets which do not provide a certain type of insurance (e.g., volatility index options), the other two may be the result of low volatility overweighting schemes. The bond-like tendency of overperforming during low real interest rates could be motivated by the effect that the equal-volatility weighting method used to form global factor portfolios provoked when overweighting less risky asset, as bonds portfolios. On the other hand, the superior adjusted performance of the commodities carry portfolio brought all the allocation methods to assign greater capital to commodities (in the global carry portfolio) and then carry (in the multi-factor portfolio). This may have delivered the same historically positive influence of commodities to inflation to multi-factor portfolios.

The traditional passive portfolio performed better in environments of high growth, low inflation, higher real interest rates and (definitely) during low volatility. In fact, as the total risk of these portfolios is predominated by equities risk (as stated in chapter 1 and proved by correlation matrices), it is not surprising to recognize that these are the scenarios in which equities perform well.

To conclude, asset allocation strategies which minimize and optimize volatility are (again) a valid choice when composing diversified portfolios of risk premia strategies. In fact, they provide a long-term insurance against the majority of the macroeconomic scenarios considered, overperforming the benchmark during favourable environments and providing parallel results to it during unfavourable ones.

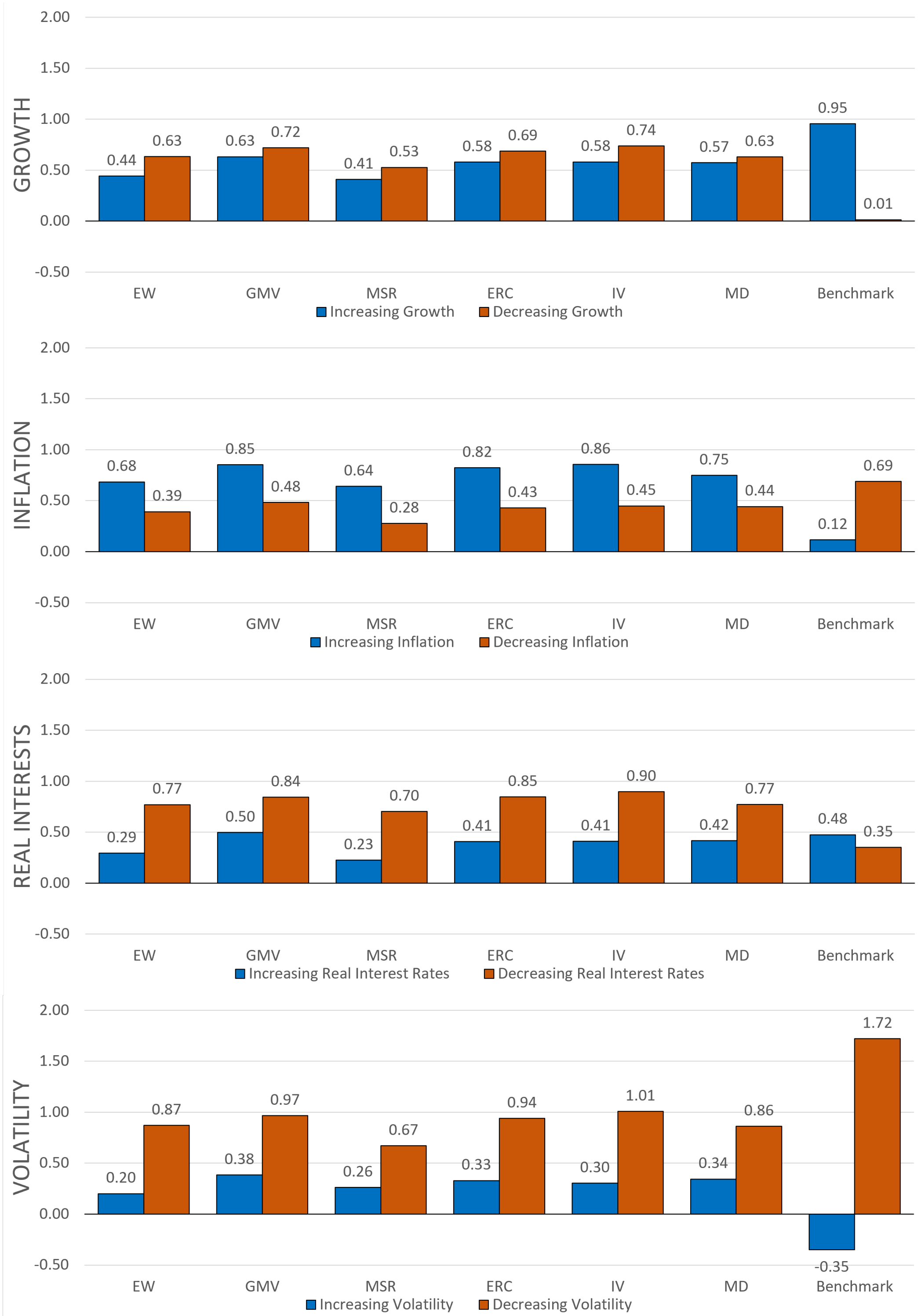

Figure 4.9: Sharpe Ratios across Macroeconomic Scenarios

Chapter 5

Conclusions

After decades of equity beta dominance across traditional passive portfolios held by institutional investors, the search for new alphas and portfolio stability brought factor investing and risk-parity strategies to dominate modern asset management. Lots of research conducted provided evidence about the profitability of these new "risk premia" strategies across the XX century. Later, the discovery of low correlation among these return premia suggested that blending them in one unique portfolio would have increased considerably the overall risk-adjusted performances.

The main objective of this thesis was to investigate the profitability of these strategies from the start of 2000 to our days and to verify the benefits of blending them in one multi-factor diversified portfolio after considered transaction costs. Comparison with a traditional passive 60/40 benchmark was also sought.

For the aforementioned sample period and the specific securities considered, results are that while individual risk premia did not provide adequate risk-adjusted over time compared to the benchmark after considering transaction costs, the multi-factor portfolios diversified across asset classes and styles provided superior performances for the entire analysis period. In particular, asset allocation methods which favoured a better management of risk provided the portfolios with the best absolute and risk-adjusted returns. Furthermore, the macroeconomic sensitivities analysis suggested that the diversification benefits embedded in these portfolios make them less exposed to macroeconomic scenarios than conventional passive portfolios.

However positive these findings, many investors keep ignoring these strategies or struggling to obtain them. In fact, to entirely implement these strategies leverage, short selling and derivatives instruments are needed. While the biggest institutional investors regularly make use of these instruments and have the resources to better manage the risks they imply, the typical investor faces technical constraints and possess general aversion to them. This is, selfishly speaking, a positive information for those big subjects which are capable of harvesting alternative risk premia and benefiting from them as recent research suggested that the most profitable and known risk premia (which are the ones considered in this thesis) have started to become overcrowded.

To conclude, the discovery of risk premia other than equity and bond premia started a new era of portfolio diversification which allowed investors to take advantage of generally risky instruments (leverage, short selling and derivatives) while maintaining target risk level under control.

Appendix A

List of main Securities

Table A.1: Summary Statistics for Individual Securities

The table provides information about 50 futures contracts across asset classes and 3 benchmark indices. From left to right the summary statistics include the instruments' name, the start date of the price series, the annualized return and the annualized standard deviation. All series end in December 2019.

Underlying	Code	Start	Ann. Ret.	Ann. Std.
Equities				
S&P/ASX 200	XP1 Index	31/05/2000	0.04	0.19
S&P/TSX 60	PT1 Index	30/09/1999	0.05	0.18
Euro STOXX 50	VG1 Index	29/01/1999	0.01	0.20
S&P 500	SP1 Index	29/09/1995	0.06	0.15
Nikkei 255	NK1 Index	29/09/1995	0.02	0.19
FTSE 100	Z 1 Index	29/09/1995	0.03	0.16
S&P/BMV IPC	IS1 Index	31/05/1999	0.01	0.22
Swiss Market Index	SM1 Index	30/09/1998	0.05	0.15
Hang Seng Index	HI1 Index	29/09/1995	0.06	0.24
NIFTY 50	NZ1 Index	30/06/2000	0.06	0.25
FTSE MIB 30	ST1 Index	31/03/2004	0.01	0.20
IBEX 35	IB1 Index	29/09/1995	0.05	0.23
DAX 30	GX1 Index	29/09/1995	0.07	0.32
CAC 40	CF1 Index	29/09/1995	0.05	0.20
Bonds				
Australian Gov. 10y	XM1 Comdty	29/09/1995	-0.01	0.07
Canadian Gov. 10y	CN1 Comdty	29/09/1995	0.03	0.07
Germany Euro Bund	RX1 Comdty	29/09/1995	0.04	0.10
US Treasuries 10y	TY1 Comdty	29/09/1995	0.03	0.06
Japan Gov. 10y	JB1 Comdty	29/09/1995	0.03	0.04

Continued on next page

Underlying	Code	Start	Ann. Ret.	Ann. Std.
UK Gilt 10y	G 1 Comdty	29/09/1995	0.03	0.07
Mexican Gov. 10y	DW1 Comdty	30/09/2003	0.03	0.08
Swiss Gov. 10y	FB1 Comdty	29/09/1995	0.04	0.05
Currencies				
AUD/USD	AD1 Comdty	29/09/1995	0.02	0.12
CAD/USD	CD1 Comdty	29/09/1995	0.00	0.08
EUR/USD	EC1 Comdty	29/05/1998	-0.01	0.09
CHF/USD	SF1 Comdty	29/09/1995	-0.01	0.10
JPY/USD	JY1 Comdty	29/09/1995	-0.03	0.10
GBP/USD	BP1 Comdty	29/09/1995	-0.00	0.08
MXN/USD	PE1 Comdty	29/09/1995	0.04	0.11
NZD/USD	NV1 Comdty	30/05/1997	0.02	0.12
NOK/USD	NO1 Comdty	31/05/2002	0.00	0.10
SEK/USD	SE1 Comdty	31/05/2002	-0.00	0.10
Commodities				
Crude Oil	CL1 Comdty	29/09/1995	0.03	0.34
Copper	HG1 Comdty	29/09/1995	0.02	0.26
Corn	C1 Comdty	29/09/1995	-0.07	0.27
Gold	GC1 Comdty	29/09/1995	0.03	0.16
Natural Gas	NG1 Comdty	29/09/1995	-0.16	0.57
Silver	SI1 Comdty	29/09/1995	0.02	0.29
Soybean	S 1 Comdty	29/09/1995	0.03	0.25
Sugar	SB1 Comdty	29/09/1995	-0.03	0.31
Wheat	W 1 Comdty	29/09/1995	-0.12	0.29
WTI Crude Oil	CO1 Comdty	29/09/1995	0.08	0.32
Live Cattle	LC1 Comdty	29/09/1995	-0.01	0.14
Lean Hog	LH1 Comdty	29/09/1995	-0.11	0.27
Feeder Cattle	FC1 Comdty	29/09/1995	0.01	0.15
Platinum	PL1 Comdty	29/09/1995	0.04	0.22
Cocoa	CC1 Comdty	29/09/1995	-0.03	0.29
Cotton	CT1 Comdty	29/09/1995	-0.09	0.27
Aluminium	AA1 Comdty	31/05/2001	-0.01	0.13
Nickel	LN1 Comdty	31/07/1997	0.03	0.34
Benchmarks				
MSCI World Total Return	M2WO	29/09/1995	0.08	0.15
Barclays Global Aggregate	LEGATRUH	29/09/1995	0.05	0.03
S&P GSCI Total Return	SPGSCITR	29/09/1995	0.00	0.22

Appendix B

Unlevered Multi-Factor Portfolio

Table B.1: Summary Statistics for the Unlevered Multi-Factor Portfolios

The table provides results about performances and statistics relative to the unlevered multi-factor portfolios obtained through six different asset allocation strategies, compared with the traditional benchmark portfolio. All returns are after transaction costs and series are from 31/12/1998 through 31/12/2019. For additional information about the statistics provided, please refer to Table 4.2

	EW	GMV	MSR	ERC	IV	MD	Benchmark
Cum. Return	38.43%	44.57%	32.57%	41.44%	42.61%	41.92%	196.29%
Ann. Return	1.55%	1.76%	1.35%	1.66%	1.70%	1.67%	5.29%
Ann. St.Dev.	1.99%	1.83%	2.14%	1.85%	1.84%	1.96%	8.50%
Sharpe Ratio	0.78	0.96	0.63	0.90	0.92	0.85	0.62
Sortino Ratio	1.07	1.55	0.88	1.35	1.37	1.25	0.78
JB Test$_{(99\%)}$	1	0	1	1	1	0	1
Skewness	-0.32	-0.04	-0.25	-0.12	-0.14	-0.18	-0.86
Exc. Kurtosis	2.08	1.02	2.30	1.22	1.65	0.95	2.95
VaR$_{(99\%)}$	1.60%	1.23%	1.75%	1.30%	1.35%	1.37%	7.81%
ES$_{(99\%)}$	2.13%	1.55%	2.36%	1.67%	1.77%	1.73%	10.49%
Max Drawdown	5.61%	5.43%	7.60%	5.37%	4.91%	6.05%	34.18%
Calmar Ratio	0.28	0.32	0.18	0.31	0.35	0.28	0.15
Ann. α	1.24%	1.52%	1.26%	1.40%	1.42%	1.41%	-
t-statistic	10.04	13.22	9.19	12.08	12.41	11.47	-
β	0.06	0.04	0.02	0.05	0.05	0.05	-
t-statistic	4.05	3.33	1.21	3.59	3.84	3.47	-
Treynor Ratio	0.27	0.40	0.71	0.35	0.33	0.34	0.05

Appendix C

Sharpe Ratios through different Asset Allocation Methods

Table C.1: Sharpe Ratios through different Asset Allocation Methods

The table provides the Sharpe ratios of the levered multi-factor portfolios obtained through six different asset allocation strategies, starting from global factor portfolios achieved through the same different asset allocation strategies, compared with the traditional benchmark portfolio. Rows indicate the allocation methods used to compose the global factor portfolios while columns the allocation methods for the levered multi-factor portfolios. All returns are after transaction costs and series are from 31/01/2000 through 31/12/2019.

		Levered Multi-Factor Portfolios						
		EW	GMV	MSR	ERC	IV	MD	Ben
Global Factor Portfolios	EW	0.67	0.92	0.74	0.87	0.83	0.90	0.57
	GMV	0.71	0.89	0.56	0.80	0.84	0.77	0.57
	MSR	0.70	0.87	0.65	0.82	0.82	0.79	0.57
	ERC	0.74	0.94	0.60	0.87	0.91	0.83	0.57
	IV	0.79	1.00	0.68	0.93	0.98	0.88	0.57
	MD	0.63	0.83	0.59	0.75	0.77	0.75	0.57

Bibliography

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, 61:259–299.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further us evidence. *Journal of Financial Economics*, 91:1–23.

Arnott, R., Harvey, C. R., Kalesnik, V., and Linnainmaa, J. (2019). Alice's adventures in factorland: Three blunders that plague factor investing. *The Journal of Portfolio Management*, 45:18–36.

Asness, C., Ilmanen, A., Israel, R., and Moskowitz, T. (2015). Investing with style. *Journal of Investment Management*, 13:27–63.

Asness, C., Moskowitz, T. J., and Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance*, 68:929–985.

Asness, C. S., Krail, R. J., and Liew, J. M. (2001). Do hedge funds hedge? *The Journal of Portfolio Management*, 28:6–19.

Bali, T. G., Cakici, N., and Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99:427–446.

Bambaci, J., Bender, J., Briand, R., Gupta, A., Hammond, B., and Subramanian, M. (2013). Harvesting risk premia for large scale portfolios. *MSCI White Paper*.

Bender, J., Briand, R., Melas, D., and Subramanian, R. A. (2013). Foundations of factor investing. *Available at SSRN 2543990*.

Bender, J., Briand, R., Nielsen, F., and Stefek, D. (2009). Portfolio of risk premia: A new approach to diversification. *The Journal of Portfolio Management*, 36:17–25.

Bhansali, V. (2011). Beyond risk parity. *The Journal of Investing*, 20:137–147.

Bird, R., Gao, X., and Yeung, D. (2017). Time-series and cross-sectional momentum strategies under alternative implementation strategies. *Australian Journal of Management*, 42:230–251.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *The Journal of Business*, 45:444–455.

Brunnermeier, M. K., Nagel, S., and Pedersen, L. H. (2008). Carry trades and currency crashes. *NBER Macroeconomics annual*, 23:313–348.

Burnside, C., M., E., Kleshchelski, I., and Rebelo, S. (2011). Do peso problems explain the returns to the carry trade? *The Review of Financial Studies*, 24:853–891.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52:57–82.

Chan, L. K., Hama, Y., and Lakonishok, J. (1991). Fundamentals and stock returns in japan. *The Journal of Finance*, 46:1739–1764.

Chan, L. K., Karceski, J., and Lakonishok, J. (1999). On portfolio optimization: Forecasting covariances and choosing the risk model. *The Review of Financial studies*, 12:937–974.

Chen, N. F. and Zhang, F. (1998). Risk and return of value stocks. *The Journal of Business*, 71:501–535.

Chopra, V. K. and Ziemba, W. T. (1993). The effect of errors in means, variances, and covariances on optimal portfolio choice. *The Journal of Portfolio Management*, 19:6–11.

Choueifaty, Y. and Coignard, Y. (2008). Toward maximum diversification. *The Journal of Portfolio Management*, 35:40–51.

Clarke, R. G., De Silva, H., and Thorley, S. (2006). Minimum-variance portfolios in the us equity market. *The Journal of Portfolio Management*, 33:10–24.

DeBondt, W. and Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, 40:793–805.

DeMiguel, V., Garlappi, L., and Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy? *The Review of Financial studies*, 22:1915–1953.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stock and bonds. *Journal of Financial Economics*, 33:3–56.

Fama, E. F. and French, K. R. (1998). Value versus growth: The international evidence. *The Journal of Finance*, 53:1975–1999.

Fama, E. F. and French, K. R. (2016). Dissecting anomalies with a five-factor model. *The Review of Financial Studies*, 29:69–103.

Ferri, R. (2010). *All about asset allocation*. McGraw Hill Professional.

Frazzini, A. (2006). The disposition effect and underreaction to news. *The Journal of Finance*, 61:2017–2046.

Frazzini, A., Friedman, J., and Kim, H. (2012). Understanding defensive equity. *AQR White Paper*.

Frazzini, A. and Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, 111:1–25.

Graham, B. and Dodd, D. (1934). *Security Analysis*. McGraw Hill.

Harvey, C. R. and Liu, Y. (2019). A census of the factor zoo. *Available at SSRN 3341728*.

Haugen, R. A. and Baker, N. L. (1991). The efficient market inefficiency of capitalization–weighted stock portfolios. *The Journal of Portfolio Management*, 17:35–40.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, 54:2143–2184.

Ilmanen, A., Maloney, T., and Ross, A. (2014). Exploring macroeconomic sensitivities: how investments respond to different economic environments. *The Journal of Portfolio Management*, 40:87–99.

Jagannathan, R. and Ma, T. (2003). Risk reduction in large portfolios: Why imposing the wrong constraints helps. *The Journal of Finance*, 58:1651–1683.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48:65–91.

Jurczenko, E. (2017). *Factor Investing: From Traditional to Alternative Risk Premia*. Elsevier.

Koijen, R. S., Moskowitz, T. J., Pedersen, L. H., and Vrugt, E. B. (2018). Carry. *Journal of Financial Economics*, 127:197–225.

Kolanovic, M. and Wei, Z. (2013). Systematic strategies across asset classes: risk factor approach to investing and portfolio management. *JP Morgan Global Quantitative and Derivate Strategy*, pages 1–205.

Lakonishok, J., Shleifer, A., and Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance*, 49:1541–1578.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, 47:13–37.

Locke, P. and Venkatesh, P. (1997). Futures market transaction costs. *Journal of Futures Markets*, 17:229–245.

Lustig, H. and Verdelhan, A. (2007). The cross section of foreign currency risk premia and consumption growth risk. *American Economic Review*, 97:89–117.

Maeso, J. M. and Martellini, L. (2017). Factor investing and risk allocation: From traditional to alternative risk premia harvesting. *The Journal of Alternative Investments*, 20:27–42.

Maillard, S., Roncalli, T., and Teiletche, J. (2008). On the properties of equally-weighted risk contributions portfolios. *Available at SSRN 1271972*.

Malkiel, B. and Jun, D. (2009). The 'value' effect and the market for chinese stocks. *Emerging Markets Review*, 10:227–241.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7:77–91.

McLean, R. D. and Pontiff, J. (2016). Does academic research destroy stock return predictability? *The Journal of Finance*, 71:5–32.

Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104:228–250.

Mossin, J. (1966). Equilibrium in a capital asset market. *", Econometrica: Journal of the econometric society*, pages 768–783.

Qian, E. (2005). Risk parity portfolios: Efficient portfolios through true diversification. *Panagora Asset Management*.

Qian, E. (2006). On the financial interpretation of risk contribution: risk budgets do add up. *Journal of Investment Management*, 4:41–51.

Ross, S. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13:341–360.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19:425–442.

Sharpe, W. F. (1966). Mutual fund performance. *The Journal of Business*, 39:119–138.

Treynor, J. L. (1961). Market value, time, and risk. *Available at SSRN 2600356*.

Winkelmann, K., Suryanarayanan, R., Hentschel, L., and Varga, K. (2013). Macro-sensitive portfolio strategies: Macroeconomic risk and asset cash-flows. *MSCI Market Insight*.