A Framework For Analysing Investable Risk Premia Strategies

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Ett ramverk för analys av investerbara riskpremiestrategier

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Abstract
The focus of this study is to map, classify and analyse how different risk premia strategies that are fully implementable, perform and are affected by different economic environments. The results are of interest for practitioners who currently invest in or are thinking about investing in risk premia strategies. The study also makes a theoretical contribution since there currently is a lack of publicised work on this subject.

A combination of the statistical methods cluster tree, spanning tree and principal component analysis are used to first categorise the investigated risk premia strategies into different clusters based on their correlation characteristics and secondly to find the strategies’ most important return drivers. Lastly, an analysis of how the clusters of strategies perform in different macroeconomic environments, here represented by inflation and growth, is conducted.

The results show that the three most important drivers for the investigated risk premia strategies are a crisis factor, an equity directional factor and an interest rate factor. These three components explained about 18 percent, 14 percent and 10 percent of the variation in the data, respectively.

The results also show that all four clusters, despite containing different types of risk premia strategies, experienced positive total returns during all macroeconomic phases sampled in this study. These results can be seen as indicative of a lower macroeconomic sensitivity among the risk premia strategies and more of an “alpha-like” behaviour.

Key-words
Risk premia, cluster tree, spanning tree, principal component analysis, macroeconomics
Ett ramverk för analys av investerbara riskpremiestrategier

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Sammanfattning
Denna studie fokuserar på att kartlägga, klassificera och analysera hur riskpremie-strategier, som är fullt implementerbara, presterar och påverkas av olika makroekonomiska miljöer. Studiens resultat är av intresse för investerare som antingen redan investerar i riskpremiestrategier eller som funderar på att investera. Studien lämnar även ett teoretiskt bidrag eftersom det i dagsläget finns få publicerade verk som behandlar detta ämne.

För att analysera strategierna har en kombination av de statistiska metoderna cluster tree, spanning tree och principal component analysis använts. Detta för att dels kategorisera riskpremie-strategierna i olika kluster, baserat på deras inbördes korrelation, men också för att finna de faktorer som driver riskpremiestrategiernas avkastning. Slutligen har också en analys över hur de olika strategierna presterar under olika makroekonomiska miljöer genomförts där de makroekonomiska miljöerna representeras av inflation- och tillväxtindikatorer.

Resultaten visar att de tre viktigaste faktorerna som driver riskpremiestrategiernas avkastning är en krisfaktor, en aktiemarknadsfaktor och en räntefaktor. Dessa tre faktorer förklarar ungefär 18 procent, 14 procent och 10 procent av den undersökta datans totala varians.

Resultaten visar också att alla fyra kluster, trots att de innehåller olika typer av riskpremiestrategier, genererade positiv avkastning under alla makroekonomiska faser som studerades. Detta resultat ses som ett tecken på en lägre makroekonomisk känslighet bland riskpremiestrategier och mer av ett alfabeteteende.

Nyckelord
Riskpremier, cluster tree, spanning tree, principal component analysis, makroekonomi
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1 INTRODUCTION

This section introduces the reader to this paper. First a background to the topic is given, followed by a presentation of the problem, research questions, purpose and contribution. Lastly, delimitations and the general disposition of the paper are presented.

1.1 Background

During the recent financial crisis, investors of all types experienced substantial losses in their portfolios. For instance, in the US, the equity wealth declined 40% during January to October 2008, from USD 20 trillion to USD 12 trillion (Gande & Senbet, 2009). The crisis has been a painful reminder of how volatile the equity markets are and the unwanted correlation of equity/bond portfolios that are supposed to be well diversified (Liinanki, 2012). Figure 1 shows the development of S&P500 and VIX during 2004-2012 and is indicative of changed market conditions, especially with a substantially higher volatility following the financial crisis.

In the past, many investors have mainly focused on portfolio constructions that are made up of equity and bond allocations alone (Passy, 2013), where the majority of the return and volatility are generated by the equity part of the portfolio. Investors have been able to rely on the equity risk premium, generated from owning stocks, in order to reach their required return and volatility targets. However,

Figure 1. Development of S&P500 and VIX between 2004 and 2012.

The figure shows the development of S&P500 and VIX between 2004 and 2012, and indicates changed market conditions after the financial crisis. The equity markets suffered severe losses during 2008-2009 and the volatility on the equity markets has been higher and more unstable after the crisis. Source: Bloomberg.
due to the correlation failures mentioned above of traditional equity portfolios and the recent low returns generated on the stock market, institutional investors and especially different pension funds have started to look for alternative investment strategies (Witham, 2012).

One of these strategies, originating from the hedge fund industry, aims to diversify through investing in multiple risk premia¹ rather than the lone equity risk premium. By using such a strategy, one would be exposed to different risk factors and hence be subject to several risk premia, compensating investors for holding risky assets. Diversifying through investing in multiple premia also helps to lower the portfolio’s overall correlation since you’re not only relying on a single source of return. The main idea is that you expose yourself to a variety of different premia on the market and by relying on more than one your portfolio benefits from diversification effects and more stable returns, making the portfolio more robust. This investment strategy is increasingly used among pension funds, where it is considered to be at the forefront of portfolio theory (NBIM, 2012).

Understanding what drives these different risk premia and how they interact during different economic phases are thus highly important for investors. This since their correlation structures and ability to produce returns during shifting economic conditions are key factors for portfolio managers to consider when constructing their investment portfolios. Analysing different risk premia will therefore be the main focus of this paper and the outcome will be useful to a variety of investors interested in risk premia strategies.

### 1.2 Problem statement

Risk premia strategies have been extensively researched (see e.g. Ilmanen, 2011; Boukhari et al., 2013; Kolanovic & Wei, 2013) in the academic literature since its breakthrough in the financial markets. However, there are large differences between risk premia studied in academic literature and investable risk premia strategies. In this paper, investable risk premia strategies are defined as strategies that exist on the market and are tradable for larger investors. These are often created by financial institutions and sold to funds to be part of their investment portfolios. The differences between risk premia in academic literature and investable risk premia are mainly due to a number of naïve assumptions that makes it difficult, and many times impossible, to actually implement the studied portfolios. Some common problems with theoretical portfolios are that there are no constraints

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¹ A risk premium is typically defined as the excess return of the risk-free rate. It compensates investors for taking additional risk, relative to a risk-free investment. An example illustrates the small cap risk premium and how to capture it: An investor investing in a small cap portfolio gets the equity market return plus the small cap risk premium. This additional return is justified by the exposure to more risky small cap assets. A portfolio that captures the pure small cap premium can be constructed by going long small caps, and short large caps. (Source: Briand et al (2009))
on the size of short positions, they are rebalanced monthly and they include all available stocks, including small caps which institutional investors often are constrained from investing in. By studying investable risk premia strategies used by AP3, our investigation is not subject to these problems.

Also, investable risk premia strategies designed to harvest the same risk premia have very different characteristics. This is caused by the many choices one face when going from theory to practice, e.g. choice of instrument (option or swap), frequency of trading (daily or monthly), rebalancing techniques (monthly or quarterly), maturity of instrument (1 month or 3 months), strike level of strategies (90 percent or 100 percent), time of day when trading (London or NY) and liquidity.

The important difference between risk premia in academic literature and in practice makes the investor’s choice of strategy and implementation as important as the choice of risk premia in portfolio construction. To be able to make optimal decisions about the strategy and implementation, an investor has to know all the characteristics of a risk premia strategy and how it is correlated with the macroeconomic environment. Even though these sorts of questions have been investigated before by others (see e.g. Bhansali et al., 2012; Kolanovic & Wei, 2013), our study addresses the problem that there is a lack of studies on investable risk premia strategies. To contribute to solve this problem, this study is based on actual risk premia strategies, used by Tredje AP-fonden (AP3), where decisions about instrument, frequency of trading etc. already have been made.

To be able to analyse investable risk premia strategies, this paper aims to answer the following research questions:

1. How can the investigated risk premia strategies be divided into groups/clusters based on differences and similarities in returns and correlation?

2. Which are the most important drivers for the risk premia strategies’ performance?

3. How do the clusters perform in different macroeconomic environments, here represented by growth and inflation and combinations of these two?

1.3 Purpose

The purpose of this study is to map, classify and analyse a subset of AP3 chosen risk premia strategies’ characteristics and performance during periods of different economic environments. The main return drivers of the strategies will also be investigated and analysed. A rigorous analysis of the above mentioned aspects is essential for AP3’s future allocation decisions since it will reveal information about their existing strategies, rather than fictive strategies constructed for a certain study.
1.4 Contribution

The results from this study are valuable for institutional investors, funds and practitioners that either invest in risk premia strategies today or want to use the results to improve their portfolios. Also those who are thinking about investing in risk premia strategies and want to gain a deeper understanding of this field can benefit from the results of this study.

This paper introduces a framework for analysing risk premia strategies. The framework makes both a practical contribution in the sense that investors can use it when analysing their own portfolios or strategies, as well as a theoretical one since there currently, to our knowledge, doesn’t exist an accepted framework for analysing risk premia strategies. The paper also contributes to the field of risk premia in general since there is a lack of publicised studies on this subject.

1.5 Delimitations

The comprehensive question regarding how to optimally allocate between risk premia strategies will not be covered in this study.

The risk premia strategies described in 2 Theoretical background have been chosen since they represent the most common premia strategies found in academic literature. There are most certainly a greater number of risk premia strategies out there than the ones addressed in this study, but they often lack detailed academic support and have therefore been left out.

1.6 Outline

The disposition of this paper is as follows: Chapter 2 explains the theoretical background relevant for this study as well as previous research done in the field. In Chapter 3, the method is described in as much detail as possible, together with a section about the data used. Motivations why the different methods were picked and limitations are also discussed. Chapter 4 contains the results from the study, while Chapter 5 presents a discussion and analysis of the results. Finally, Chapter 6 concludes the findings and gives suggestions of further research.
2 THEORETICAL BACKGROUND

This section introduces the theories and concepts used in this study, starting with an introduction to the risk premia framework and its connection to academic literature. This is followed by a definition of the main risk premia strategies and a further elaboration of the investment problems in practice. Lastly, a summary of the previous research is given.

2.1 Introduction to risk premia investing

The 2008 financial crisis exposed the limited diversification benefits of traditional assets, with the results being an abrupt increase in portfolio risk and losses. Portfolio managers could no longer rely on the equity risk premium and had to find new ways to generate returns following the low yield market that had developed in the aftermath of the financial crisis. Some investors chose to increase their allocation of high yielding assets such as equities and options with the main disadvantage being the increased risk that follows. Others chose to take a different approach, moving away from traditional assets and investments, into asset classes with lower correlation and the ability to harvest new risk premia sources (Kolanovic & Wei, 2013). This way of investing, that is the main focus of this study, is called risk premia investing, also known as factor investing, and is a concept designed to harvest returns on the market by being exposed to different sources of risk factors. The basic idea is that assets are driven by different risk factors, which the investor gets a premium for being exposed to.

Certain factors have historically earned a long-term risk premium, set to compensate the investor for the risk he takes. In order to generate stable premia, strategies are designed after sound economic rationale and their existence are well documented in academic literature. The constructed strategies all have solid explanation as to why they historically have provided a premium and are expected to continue to do so in the future (Bender et al., 2013). An example of a situation that creates an investment opportunity related to risk premia strategy is when market under-reaction or biases lead to the undervaluation of certain fundamentally sound stocks, as was demonstrated by Fama and French (1993). This creates a value premium, meaning that a premium could be obtained since a company is trading too low given certain fundamental analysis. Other premia include momentum, carry and volatility factors and will be described in more detail later in this chapter.

The risk premia approach is new to many investors but it has been used for a long time by commodity trading advisors and global hedge fund managers (Kolanovic & Wei, 2013). Strategies for harvesting these risk premia are therefore not considered a new phenomenon; they are however new in the sense that institutional investors and pension funds just recently started to move their investments more toward the risk premia rationale (NBIM, 2012).
2.2 Factors in academic literature

The theory of risk premia has been covered in academia although it is mostly the traditional equity risk premium that has been investigated. The first model used to theoretically determine the premium one gets for being exposed to systematic risk was the Capital Asset Pricing Model (CAPM), which became a foundation of modern financial theory in the 1960s (Treynor, 1961; Sharpe, 1964; Lintner, 1965; Mossin, 1966). In the CAPM, securities have only two main drivers: systematic risk and idiosyncratic risk. The systematic risk represents the risk that cannot be diversified away and is therefore rewarded with a premium. In subsequent decades after the CAPM, the notion of systematic risk steadily expanded to multiple equity factors (or risk premia) where the most influential multi-factor model, developed to describe stock returns and what underlying factors make up their premia, is the Fama-French three-factor model (Fama & French, 1993). The model explains the equity market returns with three factors: the “market” (based on the traditional CAPM model), the size factor (large vs. small capitalization stocks) and the value factor (low vs. high book to market) and is an extension of the original CAPM. In general, a factor can be thought of as a specific characteristic relating a group of securities that is statistically significant in driving their risk and returns. Although the benefits of the three-factor model are acknowledged, the Fama-French model has been subject to further improvement and today includes Carhart’s (1997) momentum factor, which has become a standard within the finance literature.

The factor and risk premia literature has, as shown above, been around for decades and studied in ample detail in order to find the drivers of equity returns. This serves as the foundation and the theoretical legitimacy of the risk premia approach covered in this study.

2.3 From risk premia to systematic strategies

There are two main camps giving alternative explanations to what makes up the risk premia that we experience in the market. The first is based on the view that markets are efficient and that premia reflect compensation for systematic sources of risk (Bender et al., 2013). The other one is based on the view that investors either exhibit behavioural biases or are subject to different constraints (Bender et al., 2013). The term systematic refers to risks that cannot be diversified away and therefore can be expected to be rewarded by a premium, this opposed to idiosyncratic risks that can be diversified away and therefore should not earn any reward (Ilmanen, 2011). The main argument for the camp that advocates the systematic risk explanation is that factors like value and momentum are affected by macroeconomic variables like growth and inflation which make them sensitive to shocks in the economy, giving them a return premium (Winkelmann et al., 2013).

The second camp assigns excess returns to certain factors because of investors’ “systematic errors”. The systematic errors can be explained by behavioural finance theory where investors exhibit
behavioural biases due to cognitive or emotional weaknesses (Bambaci et al., 2013). These biases can for instance be overconfidence, over-reacting, chasing winners or myopic loss aversion. The idea here is that if enough investors exhibit these biases, as long as it is prohibitively costly for rational investors to arbitrage these biases away, it can create anomalies that make premia in the market appear. As one can see, there are multiple theories supporting the idea behind risk premia investing, which has opened up the opportunity to create strategies around them.

The most common strategies are based on factor styles such as momentum, value, carry and volatility. They are often designed to capture alternative risk premia on the market and at the same time reduce portfolio risk. By mixing risk premia strategies with traditional market exposure one can create enhanced beta strategies by constructing an equity index that deviates from the market by for instance overweighting value and size factors or by creating an index that incorporates a momentum overlay. Investors can also create a multi-factor portfolio that incorporates several strategies and uses long-short combinations in order to neutralize factor risk. These approaches would lead to a portfolio that captures a variety of risk premia, but eliminates most of the risk factors. Risk premia strategies can therefore either be used in combination with a more traditional portfolio structure or as a single strategy of its own, all dependent on the investor’s preferences. (Kolanovic & Wei, 2013)

2.4 Definition of risk premia strategies

2.4.1 Risk factor classification

For traditional assets such as equities and bonds, the rationale for risk premia is well documented (see e.g. Fama & Bliss, 1987; Siegel, 1994; Dimson, Marsh & Staunton, 2002). The equity premium can be linked to a risk of recession in the economy and market crash, while the corporate bond premium is dependent on a company’s risk of default. These two risk premia behave similarly and tend to increase during periods of high volatility in the market (Mueller, Vedolin & Yen, 2012).

The classification of the alternative risk factors (that generate risk premia) investigated in this study will be based on the factor’s economic rationale, risk properties and behaviour in different economic environments and will be classified into five broad styles: traditional, carry, momentum, value and volatility. However, classifying risk factors is not a routine job since there are many different ways to do it. The choice of using five broad styles seems intuitive to us and this classification method is also consistent with more rigorous academic results (Kolanovic & Wei, 2013). In a perfect world, these risk factor styles should fulfil three criteria. They should be (1) independent, (2) deliver positive risk premia and (3) form a complete set. To form a complete set, they need to be able to explain the risk of any systematic strategy (span all ‘dimensions’ of risk). However, these three criteria will only hold approximately in practice. For instance, the correlation between risk factors is almost never zero, but on a portfolio level the correlations can average out to a sufficiently low level to be considered
approximately zero. An illustration of the five factor styles, fulfilling the above-mentioned criteria, used in our study is shown in Figure 2. (Kolanovic & Wei, 2013)

As mentioned earlier, the risks that are related to the risk premia of traditional assets are well understood and include tail events, economic contraction and market volatility. Alternative risk factors such as carry, momentum and value are constructed by taking long and/or short positions in traditional assets. These factors are weighted and rebalanced with the aim to capture risk premia related to certain market efficiencies, without having a direct exposure (beta) to traditional risk factors. However, the actual return of a systematic strategy will in most cases differ from the expected return due to uncertainty embedded in individual risk premia. An investor can be compensated for this uncertainty as an additional volatility premia to each of the risk factors.

Figure 2. Risk premia spanned by five factor styles.

Our illustration of five factors that fulfills the criteria of being (1) independent, (2) deliver positive risk premia and (3) form a complete set. By fulfilling these criteria they span all ‘dimensions’ of risk.
2.4.2 Traditional assets

The traditional asset classes that are traded include equities, rates (government bonds), credit (corporate bonds), commodities and currencies (Kolanovic & Wei, 2013). Additionally, given the rapid growth of derivative markets during recent years, volatility is also classified as a traditional asset class by many investors (DeLisle, Doran & Krieger, 2010; Giese 2010; Fieldhouse, 2013; Barron’s, 2013). Traditional assets are by far the most common asset classes in an investor’s portfolio and thereby constitute the core risk factors of most investment portfolios. They are also the building blocks for alternative risk factors.

Figure 3 shows the global distribution of the market capitalization of publicly traded traditional asset classes, expressed in percentage.

![Figure 3. Market size of traditional assets.](image)

The figure shows the market size of traditional asset classes globally, in percentage. Source: J.P. Morgan Quantitative and Derivatives Strategy, BIS, Bloomberg.

There are many different ways for investors to trade with traditional asset classes. Three common ways are to directly trade portfolios of stocks and bonds, trade linear derivate products such as futures, swaps and EFTs, or trade non-linear derivative products such as options. The vast majority of traditional assets are held by investors using a simple buy-and-hold strategy, which aims to capture risk premia through asset yield or long-term price appreciation.

As was emphasized in 1 Introduction, the correlation between an investor’s portfolio assets is of great importance. The correlation between traditional assets is a non-trivial subject, where the levels of correlation are influenced by many different factors such as macroeconomic, geopolitical and investor
behavioural factors. Changes in the micro-structure of the market like the introduction of new products or trading styles can also influence the correlation between traditional assets (Kolanovic et al., 2010).

Finally, when it comes to the performance of traditional asset classes, it is highly dependent on the macroeconomic environment and market technical regimes.

### 2.4.3 Carry

Carry risk factors are designed to benefit from the outperformance of higher yielding assets over lower yielding assets. A carry strategy is typically implemented by borrowing at a lower cost to fund and hold a higher yielding asset.

Carry strategies are used by investors across most asset classes, but are most popular in currencies and fixed income. Here, the carry simply comprises the differential of bond yield, or local interest rates for currencies. The currency carry is probably the most popular carry strategy, where the persistence of a return advantage for higher yielding currencies was a well-known phenomenon post Brenton-Woods in the early 1970s (Cumby & Obstfeld, 1980; Hansen & Hodrick, 1981; Meese & Rogoff, 1981; Fama, 1984; Brunnmeier, Nagel & Pedersen, 2008).

In the fixed income space, an investor can implement a carry strategy by using cash or derivative instruments. A popular rates carry strategy is to buy government bonds with the highest yield and sell those with the lowest yield.

Carry strategies are also frequently used in the credit, volatility and commodity space. During the last decade, commodity carry strategies have performed very well with a solid performance even during the crisis in 2008. However, these strategies are not commonly used in equity risk factor investing. (Kolanovic & Wei, 2013)

There are a number of risks that are common to carry strategies across assets. The most obvious risk is that higher yielding assets tend to be more risky than lower yielding ones. A common approach is thus to adjust a strategy for the assets’ volatility, called the Carry-to-risk approach.

Furthermore, carry strategies have the tendency to underperform due to certain market conditions or events such as rising volatility, cycle changes or changes in central bank policies. For instance, a weak economy may cause a depreciation in the long currency and thus make the currency carry underperform. (Brière & Drut, 2009)

### 2.4.4 Momentum

The momentum factor is a factor that reflects an excess return for stocks with a stronger past performance. In other words, stocks seem to exhibit trend over certain horizons, where winners continue to outperform and losers continue to underperform. Jegadeesh and Titman (1993) conducted
one of the first studies on momentum on the US market and found that a buy-winners-and-sell-losers strategy produced significant abnormal returns in 1965-1989. Later, in a study of mutual fund performance, Carhart (1997) included momentum in the Fama-French Three Factor Model as an additional explanatory variable, thereby expanding it to a Four-Factor Model. Rowenhorst (1998) found similar patterns regarding winners outperforming losers on a sample of 2,000 European stocks in 1978-1995. Finally, Fama and French (2012) found strong momentum returns in North America, Europe and Asia Pacific (but not in Japan) during 1989-2011 and confirmed the robustness of the Four Factor Model. This implies that momentum is a fourth persistent factor, not captured by either size or value.

Asness (1995, 1997) confirmed earlier findings on the momentum effect, but he also found another interesting property. He showed that winners and losers tend to revert over a longer horizon, i.e. losers outperform and winners underperform over a 3-5 year period. Bollen and Busse (2004) also studied momentum effects but in the setting of persistence in mutual fund performance. Their results showed evidence regarding short-time persistence and they found that the top decile of mutual fund managers generates a statistically significant quarterly abnormal return that persists for the following quarter. However, when using weekly or monthly returns, the top decile of funds does not exhibit superior performance. Empirical research upon today indicates that the strongest momentum effect is found in the following 3-12 months, after which it will likely disappear (Bender et al., 2013). This implies that a strategy aiming to capitalize on the momentum effect requires a relatively high turnover in order to work. A large 212-year backtest study was conducted by Geczy and Samonov (2013) examining the momentum strategy in the US market, where they showed that the momentum effect was statistically significant and not a product of data mining.

However, even though the empirical research is unambiguous regarding the momentum effect, the theory underlying the premium is still heavily discussed. Unlike the cases of value and size, there is no satisfactory explanation based on the efficient-market theory for the momentum effect. Instead, the theories that are most widely cited are all behavioural. Investors either over-react (Barberis, Sheleifer & Vishny, 1998; Daniel, Hirshleifer & Subrahmanyam, 1998) or under-react (Hong, Lim & Stein, 2000) to news, resulting in a momentum effect in both cases. Another more recent theory has been suggested by Vayanos and Woolley (2011) in which they propose a framework based on the dynamics of institutional investing, rather than individual biases.

As with most strategies, there are some common criticisms of the momentum strategy. These include data mining, high turnover, crowded trading and the risk of a sudden reversal which is difficult to predict and manage. The probability of a short-term reversal has been shown positively correlated with the volatility, and forecasting volatility is a very challenging task. Since momentum, like any other premia strategy, can experience an extended period of negative performance, it has been suggested
that a combination with other strategies perhaps is better than using momentum alone. Asness, Moskowitz and Pedersen (2013) found potential diversification benefits by combining value and momentum strategies, as they can be negatively correlated within and across asset classes.

2.4.5 Value
The value factor capitalizes on stocks that have low prices compared to their fundamental value and returns in excess of the capitalization-weighted benchmark. A value strategy consists of buying stocks with low prices and selling stocks with high prices, where the prices typically are determined by a ratio of some indicator of company fundamentals, such as price to book value and price to sales. Dodd and Graham (1934) were the first to write about value investing and the subject has been widely discussed since then. Value investing was later developed and formalised by Basu (1977) who found a significant positive relation between P/E ratios and average returns for US stocks that could not be explained exclusively by the CAPM. Consequently, other studies found a similar relationship between Book-to-Price ratios and average returns (e.g. Rosenberg, Reid & Lanstein, 1985; DeBondt & Thaler, 1987). The value effect has been extensively researched in its many forms, for different sample periods and for most major securities markets around the world, with the same conclusion that the effect exists. However, critics of the value premium have argued that empirical evidence is based on data mining and emphasize the sample-dependency of empirical studies (Black, 1993).

There are several theories for the existence of the value effect. The explanation based on the efficient-market view is that the value premium is a compensation for higher real or perceived risk. Cochrane (1991, 1996) and Zhang (2005) argue that value firms are less flexible and have therefore greater difficulties in adapting to unfavorable economic environments. Chen and Zhang (1998) later found that the value premium exists because value stocks are riskier, due to their high financial leverage and uncertainty in future earnings. Most recently, Winkelmann et al. (2013) developed a theory based on that value and small cap portfolios are more immediately sensitive to economic shocks, compared to growth and large cap portfolios. Consequently, the value premium can be viewed as a compensation for macro risk.

For the interested, there are also several explanations from a behavioural perspective for the value premium. The most common are based on loss aversion and mental accounting biases (see e.g. Barberis & Huang, 2001). These behavioural explanations will however not be elaborated further in this study.

2.4.6 Volatility
The volatility factor captures excess returns to stocks with volatilities, betas and/or idiosyncratic (diversifiable) risk that are less than average. The fact that a volatility premium exists is a serious puzzle since it contradicts one of the cornerstones in finance, namely that higher volatility is
associated with higher returns (Blitz & Vliet, 2007). According to the CAPM model, riskier assets should earn higher returns, but research around the volatility factor instead shows that less risky assets outperform the market (Bender et al., 2013).

There are a number of studies conducted on different markets, time periods and volatility measures that confirm the existence of the volatility factor. Some of the most important findings are summarised in Table 1.

Table 1. Previous studies.
The table shows a summary of previous studies made on the volatility factor and their main findings.

<table>
<thead>
<tr>
<th>Author/s</th>
<th>Location and time</th>
<th>Main findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haugen and Baker (1991)</td>
<td>1972-1989 US market</td>
<td>Low volatility stocks performed better than capitalization-weighted benchmark</td>
</tr>
<tr>
<td>Chan, Karceski and Lakonishok (1999)</td>
<td>US market</td>
<td>Confirmed Haugen and Baker’s results using a range of volatility measures</td>
</tr>
<tr>
<td>Jagannathan and Ma (2003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clarke, de Silva and Thorley (2006)</td>
<td>Global markets</td>
<td>All author’s found qualitatively similar results as Haugen and Baker</td>
</tr>
<tr>
<td>Geiger and Plagge (2007)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The existence of a volatility premium clearly contradicts the efficient-market hypothesis (EMH) and the assumptions of the CAPM. Most of the explanations for the volatility premium are from a behavioural perspective, where the “lottery effect” is the most common one. The lottery effect implies that people tend to take bets with a potentially small loss or a big win, where the probability of loss is much greater than the probability of win, even though the expected return may be negative. The similarity between buying a lottery ticket and a low price volatile stock then leads to investors overpaying for high volatility stocks and underpaying for low volatility stocks, due to the “irrational” preference for volatile stocks. (Bender et al., 2013)

Critics of the volatility factor argue that low volatility investing lacks an investment thesis on return, although it successfully reduces risk. Therefore, technically speaking, it should be seen as a risk management tool as opposed to an investment tool. (Bender et al., 2013)
2.5 From theory to practice

As mentioned in 1.2 Problem statement, there is an important difference between risk premia strategies in the academic literature and in practice. The standard framework used by Fama and French (1993) and many of their subsequent researchers on the field involve several assumptions that makes it difficult, and many times impossible, to actually implement the portfolios that they study. These assumptions become critical when assessing the viability of implementing the risk premia strategies for large funds, and typically institutional investors. The most important assumptions that limit investability are (Bambaci et al., 2013):

- **Long/Short portfolios**: Theoretical factor portfolios used in most studies are based on long/short portfolios, without any constraints on the size of short positions. In practice, large sizes of short positions may be difficult or impossible to hold.

- **Monthly rebalancing**: Theoretical factor portfolios are rebalanced monthly, requiring a turnover that is considerably larger than for instance institutional benchmarks.

- **Inclusion of small caps and equal weighting within portfolios**: Theoretical factor portfolios are typically constructed from all available stocks in a universe at the time, including small caps. In practice, large funds and institutional investors are often constrained from investing in certain stocks, due to for instance small size and reputation, making it impossible to replicate a theoretical portfolio. Furthermore, due to stocks being equally weighted within the factor portfolio, a significant bias towards smaller capitalization stocks is introduced.

- **No explicit liquidity or capacity constraints**: Theoretical factor portfolios are constructed without any explicit liquidity or capacity constraints. However, in index construction, capping constraints on stocks with extreme values (i.e. outliers) are not unusual.

To summarise, the extraordinary excess returns witnessed in many academic studies do not take into account several features that are central to actual implementation: transaction costs, liquidity, investability and capacity. For very large portfolios, and typically institutional investors, these omitted factors are of critical importance. In this study, we investigate risk premia in the context of real investable portfolios that have sizeable assets.

2.6 Previous research

Bhansali et al. (2012) carried out a study on how risk factors affect asset classes and how this can be used to improve the risk-parity allocation approach used by many portfolio managers. By using principal component analysis (PCA) they identified that growth and inflation accounted for 68 percent
of the variance in the co-movement of the nine different asset classes investigated in the study. The results from the PCA were also used to classify which asset classes that could be seen as pro/counter-cyclical, depending on how much of the variance that was explained by either growth or inflation. Equities and commodities was seen as pro-cyclical since they where significantly loaded on the growth risk factor, whereas bonds were considered counter-cyclical since most of the variance stemmed from the inflation factor.

In another study by Boukhari et al. (2013) they classify their strategies into three main styles:

- **Income strategies**: Aim to receive a certain steady flow of money, typically in the form of interest rates or dividend payments, e.g. equity value, FX carry, credit carry, volatility premium strategy.

- **Momentum strategies**: Act as hedge during a crisis, e.g. equity momentum, FX momentum and interest rates carry.

- **Relative value strategies**: Benefit from discrepancies across similar securities or financial instruments, e.g. credit momentum and equity dividend.

Their study showed several interesting results. Firstly, the best Sharpe ratios are found for income strategies, with equity value and FX carry strategies delivering the strongest returns. Momentum strategies tend to deliver the lowest Sharpe ratios. Secondly, the skewness for income strategies is found to be relatively large negative, while being close to zero for momentum and relative value strategies. This implies that income strategies are more likely to suffer from large losses than making large gains. Also the kurtosis (fat tails), which is a measure of extreme risk, was found to be especially high for income strategies.

A great problem for investors has been the high correlation between returns from equities, government bonds and credit, which exceeds 50 percent on average, putting a substantial limit to diversification benefits from any asset allocation strategy. In the paper by Boukhari et al (2013), they found that the average correlation between risk premia strategies was 16 percent. This compares to 50 percent observed across traditional benchmarks and about 25 percent between benchmarks and risk premia.

In their study, they also investigated how a number of strategies performed during a period of severe stress by using the latest financial and Eurozone crises as examples. Their main findings were that a number of momentum strategies performed extremely well together with – surprising to the authors – the interest rate carry strategy, this whilst other income strategies suffered heavy losses.

Another recently conducted study by Kolanovic and Wei (2013) covers how both traditional assets and risk premia behave during different macroeconomic and market-technical regimes. Performance,
volatility, tail-risk and correlations were measured during 1972-2012 and the most important results are summarised in Table 2.

Table 2. Previous studies by Kolanovic and Wei.
The table shows a summary of the findings in the paper written by Kolanovic and Wei (2013).

<table>
<thead>
<tr>
<th></th>
<th>Traditional</th>
<th>Carry</th>
<th>Momentum</th>
<th>Value</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kurtosis</td>
<td>Fat tails</td>
<td>-</td>
<td>Fat tails</td>
<td>Fat tails</td>
<td>Fat tails</td>
</tr>
<tr>
<td>Correlation with Equity beta</td>
<td>-</td>
<td>Close to 0</td>
<td>Low</td>
<td>Low or negative</td>
<td>Positive</td>
</tr>
<tr>
<td>Correlation between themselves</td>
<td>Shifting</td>
<td>Fairly low outside of major crisis</td>
<td>Relatively low, but on average positive</td>
<td>Low or negative</td>
<td>Positive</td>
</tr>
<tr>
<td>Exposure to macroeconomic regimes</td>
<td>- Heavily influenced by macro economic and market technical regimes</td>
<td>- Negatively impacted by volatility</td>
<td>- High volatility generally hurts</td>
<td>- No common patterns for value factors across asset classes</td>
<td>- Higher economic growth is generally positive</td>
</tr>
<tr>
<td></td>
<td>- The influence of macroeconomic variables differs between traditional asset classes</td>
<td>- The poor performance during the financial crisis damaged perception of carry strategies</td>
<td>- Tend to exhibit properties from underlying traditional assets</td>
<td>- Strong performance during “mid market liquidity” and sign, underperformance during low market liquidity</td>
<td>- Not very sensitive to inflation regimes</td>
</tr>
</tbody>
</table>
3 METHODOLOGY AND DATA

This section presents the methods used for answering the research questions and purpose of this study. A presentation of the data used is also provided. Lastly, the limitations and robustness of the methods are discussed.

In order to answer the research questions stated in 1 Introduction, the method has been divided into three sections: 3.1 Grouping of strategies, 3.2 Return drivers and 3.3 Cyclical variations in returns. Each section focuses on one research question, with the sections ordered after which question it aims to investigate.

Thus, the first section (3.1) will focus on how to answer the first research question by using two statistical methods, namely cluster tree and spanning tree. These methods are used as a way to distinguish similarities and differences in the data and serves as a way to categorise the strategies in our dataset.

The second section (3.2) presents the method used to investigate the second research question, namely which factors that are the most important drivers for the strategies investigated in this study.

The third section (3.3) focuses on research question number three and investigates how different risk premia strategies perform during various macroeconomic states. The macroeconomic indicators, representing different states of the economy, are made up of growth and inflation variables. All calculations and modelling in this study are done in Matlab.

3.1 Grouping of strategies

The main purpose and idea behind using a risk premia asset allocation, rather than a traditional form, is that the overall risk/return profile should be more attractive. Many of these risk premia strategies are chosen based on their historical risk and return characteristics, where the investor has to decide about the likelihood of these features remaining in the future.

First of all, to get a glimpse of the strategies’ performance and what asset class they belong to, a number of metrics based on past returns will be calculated for each strategy, including skewness, kurtosis and Sharpe ratio. Also, in order to combine risk premia strategies across different asset classes into a multi-asset portfolio, an investor needs to fully understand the risk profile of each strategy and the cross-correlation between them. To facilitate this task, the strategies will be divided into groups based on their return characteristics and correlations.

In fact, there are several ways to address the problem of cross-correlations. One popular approach is the correlation based clustering procedure (Bonanno, Lillo & Mantegna, 2001). Different algorithms
exist to perform cluster analysis in finance (e.g. Kullmann & Mantegna, 2000; Bernaschi et al., 2000; Giada & Marsili, 2001), but Lillo, Micciche and Mantegna (2005) propose a specific clustering method for stock return time series, which are similar series to those we investigate in this study. This method is a filtering procedure based on an estimation of the subdominant ultrametric\(^2\) associated with a distance that is obtained from the correlation matrix of the strategies. From this method a minimum spanning tree and a hierarchical tree, cluster tree, can be obtained. These two trees constitute a way to decompose a set of strategies into subsets of closely related strategies (clusters), without any prior knowledge of specific groups.

To summarise, the grouping of strategies will be based on the examination of the historical characteristics of each strategy, using two well-known methods for analysing data: spanning tree and cluster tree. These methods are further explained below, but in short, a spanning tree and a cluster tree are two different methods to graphically display correlations between the strategies, in this case.

The final grouping, or clustering, of the strategies will be based on the analysis of the results from the two trees, but primarily from the comparison between the two. In the best of worlds, both methods should tell the exact same story which would make the clustering easy. However, since these two methods aim to accomplish similar things in different ways, some differences in the results would not be surprising. In case of any significant differences, complicating the grouping, these will be analysed in more detail in order to find explanations for the deviations. In the end, the strategies will be divided into larger clusters based on the outcomes of these two methods. Also, the number of clusters is not decided until after the analysis of the methods. The choice of the number of clusters will be based on a trade-off between number of clusters and dissimilarity within the clusters. A large number of clusters make the analysis more complex and vague, while a high dissimilarity acceptance might result in clusters comprising strategies with deviating return characteristics.

### 3.1.1 Spanning tree

The spanning tree method used in this paper was initially invented by Mantegna (1999) as a solution to graphically visualize the increasingly complex financial system in an obvious manner. Technically, it is called a minimum spanning tree (MST) and was originally used in the field of stock returns.

The idea behind a spanning tree is quite simple. It is built by identifying the strategy that is most correlated with the other strategies, and putting it in the middle of the graph. Then it proceeds to build a number of branches, where strategies next to each other are the most correlated, in a decreasing order of correlation. When the tree is completed, strategies in the end of the branches are the least correlated and representative of the other strategies. (Boukhari et al., 2013)

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\(^2\) The concept of ultrametricity is directly connected to the concept of hierarchy and is, as such, a natural way of describing hierarchical structured complex problems. For a more detailed explanation of ultrametricity, see Ramell et al. (1986).
To construct the tree in a unique way, a measure of distance or dissimilarity between the nodes (the strategies) is needed (Suleman, 2014). In this case, the weights of the links between the nodes are based on the correlation between them. However, since the classical correlation does not fulfil axioms of Euclidean distance, the correlations are non-linearly transformed into the Euclidean distances (Gazda et al., 2013). The transformation to Euclidean distances is being done as follows:

\[ \text{Dist}(i,j) = \sqrt{2 \cdot (1 - \text{Corr}(i,j))} \quad \forall i,j \quad (1) \]

As one can see, a high correlation is transformed to a short distance and vice versa.

The spanning tree procedure provides a significant complexity reduction, where the different branches of the tree represent strategies with similar return characteristics. This grouping of strategies constitutes a suggestion for the grouping in this study, but is both analysed for plausibility and validated by the cluster tree method.

### 3.1.2 Cluster tree

The objective of cluster analysis is to cluster strategies together that are highly correlated and have little in common with other clusters. The difference between a spanning tree and a cluster tree is that whilst a spanning tree starts from a core of most representative strategies, a cluster tree instead starts with groups (or clusters). A cluster analysis allows for classifying the data in different groups, so that each strategy within a group contains similar characteristics. (Boukhari et al., 2013)

An advantage with a cluster analysis is that no assumptions regarding the probabilistic nature (or independence) between observations are needed. However, two drawbacks are that it may be difficult to determine (1) the number of clusters and (2) whether or not the clusters formed from the data significantly represent different groupings or if they are formed from randomly occurring concentrations of observations (Korobow & Stuhr, 1991).

The drawbacks with cluster analysis are mitigated in this study by (1) using a hierarchical clustering technique and (2) comparing the results from the cluster tree analysis with the results from the spanning tree analysis. The hierarchical techniques don’t have a priori assumption on the number of clusters, while the other main group of clustering techniques, partitioning techniques do. Also, even though cluster analysis is very useful in describing data, it can be merely characterised as a statistical exploratory tool (Hair et al., 1998).

The cluster tree is built from the exact same information as the spanning tree, namely the correlation distances computed by transforming the original correlations as shown in Equation (1). Again, neither spanning tree analysis nor cluster tree analysis will alone constitute the basis for the grouping of the
strategies. As mentioned, this will be done by combining the two methods, together with analytical reasoning.

3.2 Return drivers

The first research question aims to divide the strategies into clusters of similarly behaving strategies in order to improve the work of combining risk premia strategies into multi-asset portfolios. The next, highly essential part of the process of building successful portfolios is to determine which the main return drivers of the strategies are. By determining the main return drivers and how the clusters are correlated with them, investors can improve diversification and to a greater extent adjust investments according to their subjective economic forecasts.

There are several ways to estimate to what extent strategy returns are driven by common factors, such as the dynamic conditional correlation (Eagle, 2002) or copula-based dependence measures (Ignatieva & Platen, 2010). However, these two methods involve estimating the respective quantity for each pair of strategies, and then aggregating them. Instead, we use a method called principal component analysis (PCA), which has a major advantage in that it directly provides us with the relevant information for this study. Firstly, it provides us with the fraction of the variance in the data that is explained by each of the principal components and secondly, the loadings, which reflect how strong the correlation between each strategy and the component is.

PCA is a very useful method for determining a shorter list of drivers based on performance of a large list of assets. It essentially decomposes the quite complex correlation matrix into a number of common drivers or factors. PCA is a popular method for determining common drivers of return (e.g. JPMorgan, 2005) and was recently used by the European Central Bank (Bussiére, Hoerova & Klaus, 2014) in order to determine driving factors in hedge fund returns. A more detailed description of PCA and how it is used in this study follows below.

3.2.1 Principal component analysis

Principal component analysis is a classical data analysis technique that can be tracked all the way back to Pearson (1901). It can be used to compress high dimensional data sets into lower dimensional ones and is useful in visualization and feature extraction (Ilin & Raiko, 2010). Its key property, that a multitude of factors that affect a system can be summarised by a few uncorrelated composite variables, called principal components, is what makes the method so powerful (Soto, 2004). The reduction in dimensionality, that the principle components enable, are especially useful in finance since asset prices are affected by thousands of economic variables that are difficult to interpret and model with. PCA is a widely used method especially in interest rate risk analysis (see e.g. Wadhwa, 1999; Golub & Tilman,
2000) but was actually first applied in the equity markets and is still a common technique used to analyse large datasets (Soto, 2004).

In this study, the method is used to determine the main return drivers and can be decomposed into three steps. The first step is to investigate how important each principal component is. The importance of a principal component is determined by the amount of the total variance of the data that it explains. The more of the variance it explains, the more important it is. However, the number of components to account for and examine more closely is eventually up to the researcher.

Once the number of principal components is decided, the loadings or the correlations between each component and the strategies are calculated. This is done in order to help relate the principal components to macroeconomic factors. This work is analysis-based where knowledge about which factors certain strategies are positively and negatively correlated to is essential. This way, the correlations can be used to extract information and get an idea of what the principal component is related to.

The final step of the process is to combine the original strategies’ performance and the correlations with the principal component. By doing this, a graph of the principal component and its development over time can be drawn. By observing the graph and its characteristics, together with the individual correlations in step two, one could hopefully identify what macroeconomic factor the principal component in question is related to.

As described, the principal components are related to macroeconomic factors by analysing their structure and doing an ocular comparison of the principal component’s development over time versus a certain macroeconomic factor’s development over the same time frame. Another more sophisticated way of doing the comparison would be to use time series analysis in order to properly evaluate trends and seasonality that might occur in the data when a macroeconomic factor is related to a principal component. This is however not done since it exceeds the scope of this study and the overall usefulness of the procedure is considered weak in comparison to the effort needed to correctly perform a full time series analysis.

### 3.3 Cyclical variations in returns

In this section, the macroeconomic indicators used to determine how the risk premia strategies perform during shifting macroeconomic states are presented. One can always debate what macroeconomic variables to choose as the most important drivers of returns and economic shifts, but in accordance with earlier research (Ilmanen, 2010) and conventional wisdom of what affect returns, the empirical indicators chosen to represent shifting economic states are growth and inflation.
Research conducted by Bridgewater (2009) also confirms that growth and inflation are the most important determinants of asset class pricing. This is due to both these two factors’ direct impact, but also that they encompass expectations about many other relevant factors. The study concludes that “Asset class returns are largely the result of whether growth and inflation end up being higher or lower than expected, and how these expectations change” (Bridgewater, 2009).

The growth and inflation indicators are then used to divide our sample period into sections of high/low growth and high/low inflation. For these four different sample periods, returns for each cluster is calculated and compared to get an idea of how different clusters and strategies perform during different economic states. Since the clusters don’t necessarily contain equally many strategies, the performance aggregation has to be done with the purpose of getting comparable results. There are many ways to aggregate the performance of different strategies. In this study, since the greatest focus is on absolute returns, we calculate the cluster return by summing the strategies’ returns and then normalising by dividing the total cluster return with the number of strategies within the cluster. However, a way to aggregate performance with regards to risk (standard deviation) has also been considered in order to check the robustness of the results. For a more detailed explanation, see 3.6 Robustness.

Also, in the second stage of the macroeconomic investigation, the two indicators growth and inflation are divided into four economic phases that are characterised by a combination of the two factors. Table 3 below shows the name of the economic phase and the combination of growth and inflation indicators that defines the economic phase in this study. For each economic phase, the performance of each cluster will be calculated in a similar way as in the case of the two macro indicators and thereafter compared with the performance in other economic phases. Also, since the four economic phases not necessarily are of equal length, the performances of the clusters will be converted to yearly returns.

Table 3. Economic phases.

The table shows the decomposition of economic phases that are used throughout this study.

<table>
<thead>
<tr>
<th>Economic Phase</th>
<th>Growth</th>
<th>Inflation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expansion</td>
<td>Up</td>
<td>Up</td>
</tr>
<tr>
<td>Recovery</td>
<td>Up</td>
<td>Down</td>
</tr>
<tr>
<td>Slowdown</td>
<td>Down</td>
<td>Up</td>
</tr>
<tr>
<td>Recession</td>
<td>Down</td>
<td>Down</td>
</tr>
</tbody>
</table>
3.3.1 Construction of macro indicators

In order to be able to analyse the performance of strategies in high/low growth and inflation environments, definitions of these environments and how they are measured are needed. This is not straightforward since there is no unique way to measure a particular economic environment. One way of measuring economic growth is to study the relative performance of pro-cyclic industries or commodities, or even simply using equity market returns as growth indicator. However, this approach seems to have a large drawback in the closeness of the dependent and explanatory variables. In other words, the asset market returns are considered “too close” to the patterns that this study tries to explain, to form the basis for the macro indicators.

Instead, the macro indicators in this study are constructed from fundamental economic data. The approach to use macroeconomic data is chosen with the objective of capturing more fundamental relations between financial markets and underlying macro conditions. However, this can result in timing challenges as macroeconomic data are backward-looking, published with lags and subject to data revisions, while asset prices are clearly forward-looking. These concerns are very common in studies concerning asset returns or economic growth and are often mitigated by (1) using overlapping data and (2) measure the returns or growth over a longer period than the observation period (Brorsen & Harri, 2009). For example, Jones and Kaul (1996) state that they use quarterly data to deal with measurement errors in monthly data, while Britten-Jones and Neuberger (2004) argue that the use of overlapping data is based on economic reasons rather than statistical ones. In line with these authors, contemporaneous annual economic data and asset returns are used throughout this study, where past-year 12-month data with quarterly overlapping observations are used. This procedure is illustrated in Figure 4, where the indicators for an arbitrary quarter Q4 are determined by the development during that quarter together with the three preceding quarters Q1-Q3.

![Figure 4. Illustration of indicator construction.](image)

The figure shows how the two indicators, growth and inflation, are constructed. The indicators for a specific quarter are determined by the development during that quarter together with the three preceding quarters. This illustrates what we call past-year 12-month data with quarterly overlapping observations.
Each of the macro indicators consists of a data series, which are normalised by subtracting a historical mean from each observation and dividing by a historical volatility. The normalisation is mainly done to be able to make comparisons across all macro dimensions. Once normalised, ‘up’ and ‘down’ environments for each macro indicator are classified by comparing the estimated value to the median, with an estimated value greater than the median defined as an ‘up’ environment, and vice versa. This classification ensures an equal number of observations in both environments, which gives a fairer comparison when looking at cumulative returns.

The underlying series for the growth indicator are the OECD Composite Leading Indicators (CLI), which is a dataset comprising a subset of the Main Economic Indicators (MEI) database. For the inflation indicator, the underlying series are the OECD Consumer Prices (MEI), which also is a subset of the MEI database. Why these series are chosen and further details about their structure can be found in section 3.4 Data.

3.4 Data

The financial data used in this study is all of secondary nature and consists of return data from different risk premia strategies and indices. The main dataset has been provided by AP3 and consists of daily closing prices from 69 risk premia strategies, all of which are a part of AP3’s investment portfolio. AP3 has primarily collected this data from Bloomberg. The strategies are mainly based on three asset classes; equities, interest rates and foreign exchange (FX), as well as one multi-asset strategy.

The dataset spans from 2000-01-01 to 2014-04-01 and the various strategies in the dataset all have different start dates with the earliest strategies starting at 2000-01-01 and the latest strategy starting at 2013-01-21. In order to obtain a more homogeneous dataset where all strategies have a certain minimum length of continuous data, a decision was made to leave out all strategies that started after 2004-01-01, thus forcing every strategy in the sample to have at least 10 years of continuous daily returns. The sample was therefore restructured to include 46 of the original 69 strategies.

3.4.1 Indices

The indices used in this study serve as the basis for our macro indicators and since our risk premia strategies consist of assets that mainly focus on European and North American markets, indices that represent the joint development of these continents were chosen. Both the indices for growth and inflation described below use data that reflects a weighted development for all OECD member states, representing the global world economy that we are currently in. The alternative would have been to only use American data, but since the risk premia strategies are affected by events on both markets this seemed like an inferior choice.
3.4.2.1 Growth
When constructing the macro indicators for growth, an index from the OECD database called the OECD CLI index has been used. The OECD CLI is a leading indicator of global economic growth, which is the main reason for being the underlying series for the growth indicator in this study. The index shows the monthly GDP development of the OECD member states during a period from 2000-01-01 to 2014-01-01. (OECD 2014a)

3.4.2.2 Inflation
The index used to represent inflation is the OECD Consumer Price index (MEI). The Consumer Price dataset contains statistics on Consumer Price Indices, where the most relevant price statistics have been chosen to form the Consumer Price data series. This dataset is particularly useful since a lot of effort has been made to ensure that the data are internationally comparable across all countries represented and that all of them have good historical time-series data to aid with analysis. The index shows the monthly changes in consumer prices in the OECD member states during a period from 2000-01-01 to 2014-01-01. (OECD 2014b)

3.5 Limitations of method
The choice of only focusing on two macro indicators, growth and inflation, can be questioned. Even though growth and inflation have been considered the two most important drivers of returns and economic shifts, there are of course other factors like for instance monetary policy or market illiquidity that will affect returns as well. This limitation was a consequence of time constraints. However, since growth and inflation are considered to be the most important drivers of returns we feel comfortable that these two variables are enough to provide the reader with interesting results.

Another limitation arises from the fact that we have a limited data sample, ranging roughly 14 years from January 2000 to April 2014. This limitation is due to the fact that investable risk premia strategies are quite new to the fund industry, limiting our analysis to only include the most recent years.

One must also bear in mind that the subset of strategies provided to us by AP3 most likely do not reflect the entire risk premia universe since they have been actively chosen by professional portfolio managers to be a part of a fund’s investment portfolio. This might lead to a subset of strategies that are better performing than a randomly chosen one, which affects the generalizability of this study’s results to other investors.
3.6 Robustness

As mentioned in 3.3 Cyclical variations in returns, there exist many ways to aggregate performances for different strategies. In order to evaluate the robustness of our model and to investigate the case when the riskiness of the strategies are regarded, we also tested for when the performances were aggregated based on a risk-parity approach. The risk parity approach focuses on the allocation of risk rather than the allocation of capital, thus over weighting safer assets with a lower risk and vice versa for riskier assets (Asness, Frazzini & Pedersen, 2012). In this study, this procedure is as follows: Each strategy in a cluster is weighted as the inverse of its rolling 12-month standard deviation. These weights represent the ratio of the weights in a cluster, and are then adjusted so that the sum of the weights within each cluster conform. This last adjustment represents that an equal amount of money is invested in each cluster.
4 RESULTS

This section presents the results of this study. First, a summary of the risk premia strategies’ performance is conveyed. Second, the outcome of the different grouping and categorisation techniques is presented. After that, we present the findings regarding the strategies’ most important return drivers. Lastly, the results of how the risk premia strategies performed during shifting macroeconomic states are given.

The results of this study are based on the risk premia strategies being displayed below. Table 4 shows a summary of these, along with a few performance metrics. There are a total of 46 risk premia strategies with the earliest starting 2000-01-01 and the latest starting 2002-12-31. The strategies are almost equally divided among three different asset classes; equity, interest rates and foreign exchange (FX) as well as one multi-asset strategy, with all strategies ending at 2014-04-01.

Table 4. Strategy overview.

The table shows strategies used in this study. For each strategy, asset class, start and end dates as well as five performance metrics are specified.
4.1 Cluster classification

4.1.1 Cluster tree

The task of dividing the 46 strategies into larger clusters is done with help of two methods – cluster tree and spanning tree. The resulting cluster tree is shown in Figure 5, where the dotted red line has been manually drawn to ease the interpretation of the tree.

![Cluster tree]

**Figure 5. Cluster tree.**

The figure shows a cluster tree with 46 strategies divided into 4 clusters based on correlations, using correlation distances as explained in 3.1.2 Cluster tree. The red line shows the correlation distance used for the cluster categorisation. The coherent sections to the left of where the line cuts the branches make up clusters that behave similarly. The four clusters created are shown in the colours green, blue, red and orange.

First of all, the x-axis shows the dissimilarity distance between the strategies and clusters. This means that the further to the right the branches connect, the less correlated are the relevant strategies. As an example of this, one can see that the branches connecting Eq Liquidity UK and Eq Liquidity EU are the leftmost, making these strategies the most correlated.

The determination of the number of clusters is done manually and was in this case set to four. The main reason for this was to end up with a – for this study – reasonable number of clusters to analyse.
By looking at Figure 5, it is apparent that the further to the left you go and decrease the distance the number of possible clusters will grow and eventually you will end up with equally many clusters as strategies.

In short, our choice of setting the number of clusters to four gives the cluster classification illustrated in Figure 5. The number of strategies in each cluster is 15, 4, 15 and 12 from top to bottom. Worth noting from the figure is that each strategy in the blue cluster appears to be quite different from the rest of the strategies with branches that exclusively connect to the far right, indicating a substantial dissimilarity between the strategies in this cluster.

4.1.2 Spanning tree
The second step in determining clusters is the spanning tree, shown below in Figure 6. The end nodes and branches that are least correlated with the other strategies are placed along the edges of the, while the nodes in the middle of the figure represent the most correlated strategies.

The colours of the nodes are consistent with the colours of the suggested cluster classification in the cluster tree. This colouring is done with aim to ease the comparison between the trees and validate the classification suggested by the cluster tree.

As can be seen in the figure, the tree consists of many different branches and sub-branches, making it quite complicated to get a clear overview of the relationships. To divide the strategies into clusters based on this tree only, appears as a very difficult task with a great number of different feasible classifications. The final classification will instead be made below in 4.1.3 Comparison by a comparison between the cluster tree and the spanning tree.

Worth noting while observing the spanning tree alone is that most strategies aiming to harvest the same risk premia are directly connected, e.g. all FX carry strategies are connected in the upper left corner and the FX trend and momentum strategies in the middle right. This finding was expected since the procedure in the spanning tree is to connect the most correlated strategies, one by one.

4.1.3 Comparison and classification
The comparison between the cluster tree and the spanning tree are quite interesting since the two, to judge from Figure 6, are not telling the exact same story. The differences can be derived to the procedures of which the two trees are created, described in 3.1.1 Spanning tree and 3.1.2 Cluster tree.

In short, the spanning tree is built from the most representative strategies, while the cluster tree instead starts with groups or clusters.
To begin with, the blue cluster from the cluster tree is substantially scattered in the spanning tree. However, this is not as surprising as it may sound. By only observing the cluster tree it was noted that even if these four strategies; FX Liquidity, FX Value 1, FX Value 2 and IR Treasury Curve were clustered together, they were not very correlated. In the spanning tree, all of the strategies appear as end nodes, indicating a low correlation with the other strategies. Thus, even though they have a low correlation with each other, they are grouped together when starting with clusters.

The discovery that the classification of the end nodes in the spanning tree doesn’t conform with the classification in the cluster tree is present throughout the comparison between the trees, where several
end nodes seem to be misplaced, e.g. FX Momentum 3 with a orange colour in the upper right. However, these differences are caused by the different methods building the two trees. As a stand-alone strategy, FX Momentum 3 is most correlated to USD Global FX Carry, but from a cluster perspective it behaves more like the orange cluster than the green cluster.

The same reasoning can be used to explain the three nodes ERP Low Vol EU LongShort, ERP Earnings Mom EU LongShort and Eq Quality, placed in the middle of the spanning tree but in the red cluster in the cluster tree. As stand-alone strategies they have high correlations with each other but also with strategies from the green and orange clusters. However, these three strategies seen as a cluster is more correlated with the red cluster than the green or orange.

Except for the mentioned differences above, the two trees show lots of similarities in their classification of the strategies. With the explanations above, we are confident with the cluster classification suggested by the cluster tree. This classification is based on cluster similarities rather than stand-alone strategy similarities, which is in line with the aim of this study. Thus, the final cluster classification used throughout the study is shown in Table 5.

Table 5. Cluster classification.

The table shows the final cluster classification based on the 46 strategies. The strategies were divided into 4 clusters illustrated below.

<table>
<thead>
<tr>
<th>Cluster 1 - Blue</th>
<th>Cluster 2 - Orange</th>
<th>Cluster 3 - Red</th>
<th>Cluster 4 - Green</th>
</tr>
</thead>
<tbody>
<tr>
<td>FX Liquidity</td>
<td>Trend DEV FX</td>
<td>IR Spread</td>
<td>ERP FCF Yield EU LongShort</td>
</tr>
<tr>
<td>FX Value 1</td>
<td>Trend EM FX</td>
<td>Trend Bond</td>
<td>Eq Value 1</td>
</tr>
<tr>
<td>IR Treasury Curve</td>
<td>FX Momentum 1</td>
<td>Trend Money Mkt</td>
<td>Eq Low Beta US</td>
</tr>
<tr>
<td>FX Value 2</td>
<td>FX Momentum 2</td>
<td>Macro</td>
<td>Eq Low Beta</td>
</tr>
<tr>
<td></td>
<td>Efficienete Absolute Return</td>
<td>Rates Curve</td>
<td>FX Volatility</td>
</tr>
<tr>
<td></td>
<td>Trend Eq</td>
<td>IR Carry and Momentum</td>
<td>USD Global FX Carry</td>
</tr>
<tr>
<td></td>
<td>Eq Value Mom and Profitability</td>
<td>Helix Static Index</td>
<td>FX Carry and Value</td>
</tr>
<tr>
<td></td>
<td>Eq Momentum</td>
<td>IR Momentum</td>
<td>FX Carry 1</td>
</tr>
<tr>
<td></td>
<td>FX Momentum 3</td>
<td>Global Bond Carry Basket 2y</td>
<td>FX Carry 2</td>
</tr>
<tr>
<td></td>
<td>EQ Liquidity US</td>
<td>Global Bond Carry Basket 10y</td>
<td>FX Carry 3</td>
</tr>
<tr>
<td></td>
<td>EQ Liquidity UK</td>
<td>Rates Duration Neutral Carry</td>
<td>IR Volatility EU</td>
</tr>
<tr>
<td></td>
<td>EQ Liquidity EU</td>
<td>Global Kronos Index</td>
<td>IR Volatility US</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ERP Earnings Mom EU LongShort</td>
<td>Rates Implied Volatility</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ERP Low Vol EU LongShort</td>
<td>Rates Liquidity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Eq Quality</td>
<td>Eq Value 2</td>
</tr>
</tbody>
</table>
4.2 Return drivers

PCA provides an efficient way of summing up the information in a correlation matrix and decompose it into a series of return drivers. In this section, PCA analysis is applied to the strategies in order to determine the main return drivers.

4.2.1 Amount of variance explained

The first step in the PCA analysis is to identify the principal components and how much of the variance each of the components explains. Figure 7 shows the amount of the total variation of the data explained by the components. Important to notice is, what each of the principal components is related to is unknown in this step of the analysis.

As one can see in the figure, the first principal component (whatever that may be) explains almost 18 percent of the total variation of the data, the second explains roughly 14 percent and the third about 10 percent. The remaining components each explains below 10 percent of the total variance and as many as 21 components explain at least 1 percent of the variation in data. The first three components, explaining 10 percent or more, account for about 42 percent of the total variance and are further examined below in order to understand what they are related to. Components explaining less than 10 percent are considered less important and are not investigated further in this study.

**Figure 7.** PCA variance.

The figure shows the amount of the total variation in the data explained by the principal components. Each bar represent a principal component and the height corresponds to the amount of the total variance each component explains.
4.2.2 Determining principal components and correlations

Figure 8 shows the strategies’ loadings, or the correlations, to the first principal component. The correlation is useful for two things; firstly, it helps in the work of identifying what the first principal component might be, and secondly how each strategy is related to the principal component once it is known.

Bars with a positive sign indicate a positive correlation, with the height of the bar indicating the strength of the correlation. As one can see, there are roughly equally many strategies that are positively correlated to the first principal component as there are negatively correlated.

Looking at which strategies that are most correlated with the first principal component, one finds that the nine most positively correlated strategies all belong to cluster 3. In case of negative correlation, the eight most negatively correlated strategies belong to cluster 4 and cluster 2. A more detailed look reveals that it is the FX carry strategies from cluster 4 and the equity liquidity strategies from cluster 2.

In Figure 9, a graph of the first principal component is drawn. The black line shows the first principal component’s performance during the sample period, which by a quick look exhibits some interesting patterns. Most noteworthy is the extreme spike in the end of 2008, coinciding with the start of the
financial crisis. The red line shows the development of a volatility index (VIX) and has nothing to do with the PCA. It has been added to allow for a comparison between the graphs and shows a clear resemblance to the behaviour of the first principal component. The similarities in movements over time lead us to believe that the first component is related to market volatility and could be seen as a volatility or crisis factor.

Figure 9. PC1 analysis.

The black line shows the performance of the first principal component for the complete sample period (2000-01-01 to 2014-04-01). The red line shows the volatility index VIX. Source: Yahoo Finance.

Figure 10 shows the strategies’ correlation to the second principal component. In contrast to the case of the first principal component, a large majority of the strategies are positively correlated to this component. Also, only one strategy has a negative correlation exceeding 0.1.
Figure 10. Coefficients for PC2.

The figure shows the strategies' correlation to the second principal component. Direction of the bar (up or down) shows the sign of the correlation, while the height indicates the strength of the correlation.

Here, 11 of the 14 most positively correlated strategies belong to cluster 2. Since the entire cluster consists of 12 strategies, it’s apparent that cluster 2 is strongly correlated with the second principle component. On the negative side, the five most negatively correlated strategies belong to cluster 4.
The performance graph for the second principal component is drawn in Figure 11. As for the first component, the black line shows the second component’s performance during the sample period, which displays quite a different pattern compared to the first component. Observe that the y-axis for the component’s performance has been inverted in order to find a good resemblance with a macro factor driving the returns. In this case, the inverted component seems to be less volatile with more distinct trends and has a trough\(^3\) instead of a peak in late 2008, early 2009. The red line shows the performance of S&P500, an index used in this study to represent the direction of the equity market. The component’s resemblance to S&P500 over time shows that it is affected by the movements of the equity market and is therefore found to be an equity directional factor.

Figure 12 shows the strategies’ correlation to the third principal component. In this case, there are again many more positively correlated strategies, however there are a handful of strategies that are significantly negatively correlated as well.

\[^3\text{Opposite of peak. The lowest turning point of a business cycle.}\]
The patterns in this case are not as clear as in the previous cases. The seven most positively correlated strategies are dominated by cluster 4, but include two strategies from cluster 3 as well. Beyond the most positively correlated strategies, a series of momentum strategies from cluster 2 also appear as positively correlated to the third principal component. However, the equity liquidity strategies from cluster 2 form three of the most negatively correlated strategies.

The performance graph for the third principal component is drawn in Figure 13. As for the other two components, the black line shows the third component’s performance during the sample period, which again displays quite different patterns compared to the first two components. Observe that the y-axis for the component’s performance again has been inverted. The inverted component seems to be quite high from 2000 until 2002, experiencing a low from 2002 until the end of 2008 when it reaches a higher level again. The red line shows the level of the 10 year US interest rate over the period, which was found to resemble the component in behaviour. The third principal component has therefore, through analysis and visual inspection, been found to be an interest rate factor.
Figure 13. PC3 analysis.

The black line shows the inverted performance of the third principal component for the complete sample period (2000-01-01 to 2014-04-01). The red line shows the 10 year US interest rates for the same period. Source: OECD.
4.3 Macro performance

This section presents how the different clusters of risk premia strategies performed when being exposed to shifting macroeconomic environments, here represented by inflation and growth. First, inflation and growth effects are treated and presented separately. Then the results of the combined effects, represented as different economic phases, are reviewed.

4.3.1 Cluster performance in growth environments

Figure 14 shows the performance of our four different clusters. The blue sections display periods when the macro indicator for growth is ‘up’ and the white sections when it’s ‘down’. The environments for each macro indicator are classified by comparing the estimated value of growth to the median, with an estimated value greater than the median defined as an ‘up’ environment, and vice versa. For a more detailed description, see section 3.3.1 Construction of macro indicators.

The performance is based on the data sample ranging from 2000-01-01 to 2014-01-01. Figure 14 however only shows the performance for the period 2000-09-01 to 2013-09-01. This is because a technique of past-year 12-month data with quarterly overlapping observations is used when
constructing our macro indicators, which forces the reduction of the sample. This was described more in detail in 3.3.1 Construction of macro indicators.

Figure 14 shows a positive performance for all clusters and all but cluster 3 tend to perform better during ‘down’ than ‘up’ growth environments. A noteworthy pattern however is that all clusters still have a positive return during both periods. A more detailed breakdown of the different clusters’ cumulative returns is shown in Table 6.

Table 6. Cluster returns in growth environments.
The table shows a numerical breakdown of the different cluster performances during ‘up’ and ‘down’ growth environments.

<table>
<thead>
<tr>
<th></th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
<th>Cluster 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Growth Up</td>
<td>17.55%</td>
<td>26.51%</td>
<td>43.03%</td>
<td>28.14%</td>
</tr>
<tr>
<td>Growth Down</td>
<td>41.93%</td>
<td>56.54%</td>
<td>29.94%</td>
<td>38.80%</td>
</tr>
</tbody>
</table>

4.3.2 Cluster performance in inflation environments
Figure 15 below shows the performance of our four different clusters. The difference here is that the clusters now have been evaluated considering shifting inflation environments instead of growth. The blue sections display periods when the macro indicator for inflation is ‘up’ and the white sections when it’s ‘down’, where the classification of the macro indicators is done in the same way as for growth. The performance is based on the data sample ranging from 2000-01-01 to 2014-01-01.
Figure 15 shows an overall positive performance for all clusters, with clusters 1 and 3 performing better during ‘down’ inflation environments and clusters 2 and 4 performing better during ‘up’ environments. A more detailed breakdown of the different clusters’ performance is shown in Table 7.

Table 7. Cluster returns in inflation environments.

<table>
<thead>
<tr>
<th></th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
<th>Cluster 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inflation Up</td>
<td>17.64%</td>
<td>43.49%</td>
<td>31.45%</td>
<td>42.49%</td>
</tr>
<tr>
<td>Inflation Down</td>
<td>41.82%</td>
<td>37.94%</td>
<td>41.39%</td>
<td>24.82%</td>
</tr>
</tbody>
</table>

4.3.3 Economic phases

The different clusters were also assessed during a combination of the two macro indicators, growth and inflation, making it four separate economic phases to investigate. The four phases and what they imply for our macro indicators are shown in Table 8.
Table 8. Economic phases.

The table shows the decomposition of economic phases that are used throughout this study.

<table>
<thead>
<tr>
<th></th>
<th>Growth</th>
<th>Inflation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expansion</td>
<td>Up</td>
<td>Up</td>
</tr>
<tr>
<td>Recovery</td>
<td>Up</td>
<td>Down</td>
</tr>
<tr>
<td>Slowdown</td>
<td>Down</td>
<td>Up</td>
</tr>
<tr>
<td>Recession</td>
<td>Down</td>
<td>Down</td>
</tr>
</tbody>
</table>

Figure 16 shows how our sample is divided among the different economic phases. A reference index showing the S&P500 development has also been added to illustrate the movements of the US equity market. A slowdown period is evident after the IT-bubble of -00, which is then replaced by periods of economic recovery and expansion. Clear signs of the financial crisis of -08 can also be found where a phase of slowdown is seen in -07 leading up to an economic recession in the latter part of -08. Slowdown and recession periods are also found between -11 and -13 in connection to the European debt crisis that followed after the turmoil of the financial crisis.

Figure 16. Economic phases in the data sample

The figure shows a breakdown of the different economic phases in our sample. The different phases are shown in descending colours of blue. The black line shows the movement of the S&P500 during the same period and is added as a reference index.
The economic phases are constructed by combining the information from the macro indicators. This led to the expansion and recession phases being made up of 10 periods each and the recovery and slowdown phases of 16 each. In order to make the phases of different length comparable, the returns were normalised to yearly returns.

4.3.4 Expansion

The expansion phase is made up of all three-month periods that meet the requirements of an economic expansion phase, meaning that both the inflation and growth indicators were ‘up’ during this time. Figure 17 shows the combined cumulative returns during all the phases of economic expansion found in our sample. This means that the x-axis doesn’t necessarily follow a continuous time-span but is rather a composition of different time periods when the condition of economic expansion was met.

During the periods of expansion in the sample, cluster 2 performed the best yielding a return of 12.79 percent, as opposed to cluster 1, which performed the worst of the four, yielding a return of 2.71 percent. All clusters however show positive returns when the entire expansion sample is considered.

![Figure 17. Cluster return during expansion.](image)

The figure shows the cumulative returns for the four clusters during the expansion phases in our sample. The x-axis is made up of ten 3-months periods, not necessarily continuous in time but rather a composition of all expansion phases in the sample.
4.3.5 Recovery

Figure 18 shows the combined cumulative return during the phases of economic recovery found in our sample. Here, cluster 4 performs the best with a return of 27.54 percent, yielding a slightly higher return than cluster 2. The worst performing cluster was, as in the case of expansion, cluster 1 which yielded a return of 14.53 percent. Cluster 2 and 4 outperformed cluster 1 and 3 both in recovery and expansion phases with the common denominator being that growth was ‘up’ during these phases. When considering the entire recovery sample, all clusters showed a positive total return.

![Recovery graph]

Figure 18. Cluster return during recovery.

The figure shows the cumulative returns for the four clusters during the recovery phases in our sample. The x-axis is made up of sixteen 3-months periods, not necessarily continuous in time but rather a composition of all recovery phases in the sample.

4.3.6 Slowdown

Figure 19 shows the combined cumulative return during the phases of economic slowdown found in our sample. Here cluster 3 outperforms the other clusters with a return of 29.90 percent. The worst performing cluster was cluster 2 which yielded a return of 12.17 percent. During the slowdown phase, as opposed to expansion and recovery phases, cluster 3 are the highest performer.
Figure 20 shows the combined cumulative return during the phases of economic recession found in our sample. In this case, cluster 1 performs the best with a return of 23.92 percent, yielding a slightly higher return than cluster 2. The worst performing cluster is cluster 4 which yielded a return of 8.82 percent, just beaten by cluster 3 with a return of 8.85 percent.

Table 9 shows a more detailed breakdown of the different clusters’ performance during the economic phases presented above. Here the returns have been normalised in order to deal with the fact that different phases had different length. The table shows the same scenarios that were presented above but now with normalised yearly returns, enabling comparisons between phases of different length.
Figure 20. Cluster return during recession.

The shows the cumulative returns for the four clusters during the recession phases in our sample. The x-axis is made up of ten 3-months periods, not necessarily continuous in time but rather a composition of all recession phases in the sample.

Table 9. Yearly cluster returns during economic phases

The table shows the yearly cluster returns during our four different economic phases. Normalisation has been made in order to enable comparisons between the phases.

<table>
<thead>
<tr>
<th></th>
<th>Cluster 1</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
<th>Cluster 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expansion</td>
<td>1.08%</td>
<td>4.93%</td>
<td>3.93%</td>
<td>4.53%</td>
</tr>
<tr>
<td>Recovery</td>
<td>3.45%</td>
<td>6.20%</td>
<td>4.53%</td>
<td>6.27%</td>
</tr>
<tr>
<td>Slowdown</td>
<td>3.43%</td>
<td>2.91%</td>
<td>6.76%</td>
<td>3.49%</td>
</tr>
<tr>
<td>Recession</td>
<td>8.96%</td>
<td>8.62%</td>
<td>3.45%</td>
<td>3.44%</td>
</tr>
</tbody>
</table>
5 DISCUSSION AND ANALYSIS

This section provides more in-depth analysis of the results of this study. First, the results of the cluster classification are discussed. Second, the three principal components extracted from the PCA are analysed, explaining the return drivers further. Lastly, the results from the macro analysis are treated, shedding more light on potential reasons for why the clusters performed the way they did.

5.1 Cluster classification

The cluster classification was done by a comparison between the cluster tree and the spanning tree. However, decisions concerning where to place certain strategies and even more important the number of clusters is all up to the researcher.

One advantage with more clusters is that the strategies in each cluster resemble each other to a greater extent. The correlation distances within the cluster decrease and one can be more certain that the smaller clusters behave more similar during different economic conditions. However, the aim with the cluster classification approach is to reduce the high-dimensional data into a low-dimensional one in order to get an overview of the behaviour of the strategies and to ease the analysis. Also, if the number of clusters is increased so that strategies in each cluster are highly correlated, the key part of finding strategies that behave similarly even though they aim to harvest different risk premia in different asset classes diminish.

In this study, the number of clusters was determined to four with the intention to reduce complexity and ease the analysis. However, when examining the differences in the cluster tree and spanning tree mentioned in 4.1.3 Comparison and classification, one can see that the three orange nodes; Eq Liquidity UK, Eq Liquidity EU and Eq Liquidity US, and the three red nodes; ERP Low Vol EU LongShort, ERP Earnings Mom EU LongShort and Eq Quality, that look misplaced, actually would have formed two separate clusters if the number of clusters was increased. The choice of having four clusters was based on a trade-off between number of clusters and dissimilarity within the clusters, as discussed earlier in the study.

5.1.1 Properties of clusters

Finding some patterns in the cluster classification regarding what type of strategies dominate each cluster would facilitate the analysis and give rise to a deeper and more interesting discussion. Both the correlations with the main return drivers and the clusters’ performance during different economic environments would be better understood with a greater chance of finding explanations for the results if some general properties of the clusters were known.
A quick look at the cluster classification in Table 5 reveals that the blue cluster, cluster 1, is a mix of strategies that are not very correlated with each other or any other cluster. Therefore, any general properties of this cluster are not found and it is defined as a random cluster.

The orange cluster, cluster 2, is dominated by momentum strategies. As many as 8 out of 12 strategies implement either a FX or equity momentum/trend strategy, while 3 are equity liquidity strategies with an, apparently, similar behaviour as the momentum strategies. Thus, cluster 2 seems to be dominated by momentum strategies.

The red cluster, cluster 3, is dominated by strategies focused on interest rates. The asset class in focus for every strategy can be found in Table 4 that lists all strategies with several characteristics. The actual risk premia these strategies are set to harvest differ among the interest rate strategies but include carry, momentum and curve strategies. Thus, cluster 3 seems to be dominated by different strategies based on interest rates.

The green cluster, cluster 4, is a mix of asset classes containing equity, FX and interest rate based strategies. However, 8 of 15 strategies in this cluster implement some kind of carry strategy, while the others are primarily equity value or equity low beta strategies. Cluster 4 seems therefore dominated by carry strategies.

5.2 Return drivers

The first result of the principal component analysis showed that only three components explained 10 percent or more, while many components explained at least 1 percent of the variation in the data. In decreasing order, the three components explained about 18 percent, 14 percent and 10 percent of the variation. The identification of what these components correspond to can be divided into two steps. Firstly, deep knowledge about the strategies enable us to get an idea of what each component is related to through analysing the coefficients, namely the strategies’ correlations with each component. Secondly, looking at the performance of the component and trying to identify patterns could also lead to ideas of economic factors with similar patterns.

By studying the two figures (Figure 8 and Figure 9) for the first component that explains 18 percent of the variance, some findings were highlighted and summarised in 4.2.2 Determining principal components and correlations. Firstly, the nine most correlated strategies with the first principal component belonged to cluster 3. Secondly, the FX carry strategies belonging to cluster 4 were among the most negatively correlated strategies. Together with the findings about the performance graph that had one of its peaks during the financial crisis 2008, the first principal component seems to be some kind of crisis factor. This is the reason for plotting the component’s performance versus the volatility index VIX.
By comparing the two graphs in Figure 9, one can identify many similarities between the two. Important to notice is that the amplitude of the graphs is not important or in focus, but rather the directions. As mentioned in 2 Theoretical background, FX carry strategies tend to perform badly during economic turmoil and crises (Kolanvic & Wei, 2013), making its negative correlation to the crisis factor reasonable. It also seems quite reasonable that interest rate strategies are positively correlated with a crisis factor. The explanation for this will be presented in the discussion covering the macro performance, 5.3 Macro performance.

Next, for the second principal component explaining 14 percent of the total variation, it was found that a large majority of the strategies were positively correlated to this component. The most positively correlated strategies belong to cluster 2, which is a cluster dominated by momentum strategies. The performance of the second component experienced a substantial decline during the financial crisis, suggesting a relationship with the stock market. A comparison between the two graphs in Figure 11 reveals many similarities with regards to the direction of the two graphs. However, the development up until 2006/2007 differs a lot and is hard to explain. Nevertheless, this factor seems most related to the direction of the equity markets, with a similar behaviour after 2008.

The results for the third principal component, explaining 10 percent of the total variance, revealed that the most positively correlated strategies belong to cluster 4. Among these, the FX carry and IR momentum strategies are found. These are strategies that flourish when interest rates are moving, creating opportunities for capitalizing on mispricing and market anomalies. This suggests that the third principal component is related to the direction of the interest rate, why the US interest rate has been plotted against the third principal component. The directions of the two graphs seem to correspond quite well, except for a short period around 2009. Nevertheless, by the reasons given above, the third principal component is found to be related to the level of the interest rates.

5.3 Macro performance

When analysing the results from our macro-driven return analysis we could see that the clusters performed quite differently depending on what type of environment they were in. We could for instance see that during expansion and recovery phases, two phases related to higher growth and a more bullish economic outlook, clusters 2 and 4 performed the best. In the case of cluster 2 this could be explained by the fact that it contains quite a lot of momentum strategies that follow the market trends more closely, giving rise to higher returns during more expansive phases of the economy. Similar results were also found by Griffin, Ji and Spencer (2005) who concluded that momentum strategies experience positive returns during both market expansion and contraction. When it comes to cluster 4, a cluster made up of a lot of carry strategies, the positive performance can be explained by the fact that carry strategies tend to outperform when growth and inflation is high (Kolanovic & Wei, 2013), traits that were seen during both expansion and recovery phases.
Looking at the slowdown phase one could see a different pattern. In this phase, cluster 3 that was among the worst performing during expansion and recovery, were now the best performing. The positive results of cluster 3, that contains a lot of interest rate strategies could be explained by the fact that the last slowdown periods seen in our sample correspond to the debt crisis that emerged in Europe in the aftermath of the financial crisis. This was a time when the treasury rates and bond markets experienced high volatility and many times abnormally high treasury rates, Greece being one example. High government rates and large deviations in countries’ interest rates create more attractive investment situations than if the interest rate market would be stable. The other clusters performed quite equal, with returns ranging between 12-15 percent.

When it comes to the recession phase, a phase made up by periods right after the financial crisis and periods around the European debt crisis, the best performing cluster was cluster 1. This cluster is harder to analyse since it contains quite diverse risk premia. However, one possible explanation as to why the cluster performed so well could be just the fact that it actually does contain quite different and uncorrelated risk premia strategies. Uncorrelated and diverse assets are less affected by movements in the markets, which could explain why cluster 1, which seems to possess these qualities, performed the way it did.

Another top performing cluster during the recession phase was cluster 2, which contains plenty of momentum strategies. Since momentum strategies are trend-following by nature the worst type of markets unfold when volatility is high and clear trends fail to establish (Daniel & Moskowitz, 2013; Kolanovic & Wei, 2013). This was however not the case after and around the financial crisis and European debt crisis when the recession phases took place. A downward trend ruled which enabled the momentum cluster to capitalize on the falling markets. The positive results for momentum strategies in times of recession and crisis can also be explained by the fact that momentum strategies generally have a positive correlation with illiquidity (Smith, 2010), meaning that the illiquid markets that was experienced after and around the financial crisis and European debt crisis actually worked in favour of momentum strategies. The worst performing cluster was cluster 4, a cluster containing a lot of carry strategies. This was in line with previous findings, that carry strategies have a tendency to unwind during market shocks, show poor results in relation to the financial crisis (Kolanovic & Wei, 2013) and be heavily affected by volatile markets (Christiansen, Ranaldo & Söderlind, 2009).

The differences in performance during the various economic states open up for diversification opportunities among the different clusters. Although the returns for the different clusters were quite stable, we could observe clear patterns concerning how the underlying risk premia was affected by the different macro variables growth and inflation. This is important for investors of all types, especially if you are engaged in portfolio construction and wants to benefit from diversification effects.
A general but noteworthy observation is that all clusters, although representing quite different styles of risk premia, experienced positive total returns during both ‘up’ and ‘down’ inflation and growth environments. This was also true for our four different economic phases. These results can be seen as indicative of a lower macroeconomic sensitivity among the risk premia strategies and more of an “alpha-like” behaviour. These results are also in line with the academic view that risk premia investing historically has provided a quite stable premium and is expected to continue to do so in the future (Bender et al., 2013). An important difference between the results in this study and a lot of the previous literature (Bender et al., 2013; Kolanovic & Wei, 2013) is that our results are based on actual investable risk premia strategies used by AP3 and other investors on the market, not just theoretical examples or studies made on broad indices. The positive results regarding our cluster returns could therefore be seen as further strengthening the field of risk premia investing.

5.3.1 Robustness
The concept regarding how to design an optimal portfolio has undergone dramatic changes over the last few decades. Numerous studies have revealed that asset allocation is key to investment performance over time (Brinson, 1986; Ibbotson & Kaplan, 2000; David et al., 2007). However, how to optimally allocate between assets is a comprehensive question and not regarded in this study. Nevertheless, in an attempt to strengthen and validate the robustness of our results, the study of the clusters’ macro performances was repeated with another allocation technique, namely a risk-parity allocation. We believe that the results using this technique are of great interest for investors since risk, in this case represented by standard deviation, is a regarded parameter in the allocation procedure.

The results for the two allocation techniques during shifting growth and inflation environments can be found in 8 Appendix. The results were very positive in the sense that the similarities between the two cases were striking. However, as expected when using two different allocation techniques, there were also some differences. In general, the main difference was that the return levels were in most cases lower when using the risk-parity allocation, as opposed to the equally weighted allocation. The intuitive explanation for this finding is that, in the case of a risk-parity allocation, riskier strategies with higher volatilities and thus greater movements are less weighted, while the safer assets are more heavily weighted. In our case of stable positive performances, the allocation with equal weight tends to perform better from an absolute return perspective. However, this allocation may result in very risky portfolios that violate the requirements of larger investors’ portfolios, and typically institutional investors’.

In short, the clusters’ performances were very similar for both allocation techniques. A quite stable and positive performance was found for most clusters in the two cases, with no cluster experiencing a negative performance in any specific growth or inflation environment for the entire sample period.
Based on these findings, we conclude that these results are indicative of a robust macro performance method.

5.4 Sustainable development

The results of this study will contribute to the general understanding of risk premia investing, a type of investment strategy that is believed to increase in popularity during the years to come, especially by institutional investors and funds. Gaining more knowledge about this field is therefore important if one wants to make sustainable investments that manage to not jeopardize either investor’s funds or the financial stability of the markets and the economy as a whole. The financial crisis had a great effect on the world’s economic growth and preventing similar scenarios from happening again requires more in-depth knowledge of the investments one is making and what to expect from them during shifting economic outlooks. The results of this paper will contribute to a more knowledgeable and in turn a more sustainable development of the financial sector.
6 CONCLUSIONS

This section summarises the results and connect them to the initial problems that this study aimed to answer. First, a presentation of the main results and how they connect to the research questions stated at the beginning is given. Lastly, some reflections and suggestions to further research are given.

The purpose of this study was to map, classify and analyse a set of risk premia strategies during shifting economic environments. In particular, the study aimed to answer the research questions concerning (1) how the investigated risk premia strategies can be divided into clusters, (2) the most important drivers of returns and, (3) how the risk premia clusters perform in different macroeconomic environments, here represented by growth and inflation.

A combination of the statistical methods cluster tree, spanning tree and principal component analysis were used in order to categorise the investigated risk premia strategies into different clusters based on their correlation characteristics and to find the strategies’ most important return drivers. The analysis continued by investigating how the different clusters performed during four economic phases; expansion, recovery, slowdown and recession. The combined methods and analysis approach in this study constitute a framework that we suggest to be a powerful and rigours way for investors to evaluate risk premia strategies when facing investment and portfolio decisions.

The empirical findings of this study showed that by using the cluster and spanning tree techniques, the risk premia strategies could be divided into four main clusters. Cluster 1 was a mix of four not so correlated strategies, cluster 2 was a momentum cluster, cluster 3 were based on interest rates and cluster 4 was dominated by carry strategies.

The results further showed that the three most important return drivers were found to explain 18 percent, 14 percent and 10 percent of the total variation of the data, respectively. The work of identifying what the factors were related to was done by analysing positively and negatively correlated strategies with each principal component, together with a study of the factors’ performance over the sample period.

The first principal component was found to be closely related to the volatility index VIX and was concluded to be a crisis factor. The strategies’ correlations with the first factor further strengthened the hypothesis that it would be a crisis factor. Thus, the most important return driver, explaining the greatest part of the variation in the data, is a crisis factor.

For the second principal component, the results didn’t reveal as clear patterns as for the first principal component. However, analysing the correlations between the second factor and the strategies, together with the factor’s performance with a substantial decline in 2008, indicated a relation to equities. Thus,
the second most important return driver was concluded to be related to the direction of the equity market.

By using the same procedure for identifying the third principal component, it was found to be closely related to the movement of the interest rate. The directions for the third component and the US interest rate seemed to correspond well, except for a short period during the crisis in late 2008. Thus, the third principal component was concluded to be related to the movement of the US interest rate.

When it comes to the question of how the clusters performed in different macroeconomic environments the study showed that all clusters, despite containing quite different risk premia strategies, experienced positive total returns for all four economic phases. These results can be seen as indicative of a lower macroeconomic sensitivity among the risk premia strategies and more of an “alpha-like” behaviour. This is exactly the result an investor expects when investing in risk premia strategies. Similar results were found by Ilmanen, Maloney and Ross (2014) who concluded that risk premia have meaningfully less macro exposure than traditional asset classes.

Although the returns for the different clusters were all positive, one could observe clear patterns regarding how the underlying risk premia was affected by the different macro variables. For instance momentum strategies, represented by cluster 2, performed the best during economic phases with high growth like expansion and recovery in the economy. Cluster 2 also performed well during recession phases, most likely due to the fact that trend-following momentum strategies are able to capitalize on both down and upwards markets, as long as there is an overall market trend. The findings that momentum strategies seem to perform well during both times of recession and expansion are in line with previous studies made by Griffin, Ji and Spencer (2005).

Cluster 3 on the other hand, performed the worst during the recession phase, a result found to be in line with previous studies and explained by the fact that carry strategies have a tendency to unwind during market shocks (Christiansen, Ranaldo & Söderlind, 2009; Kolanovic & Wei, 2013). When it comes to slowdown periods, interest rate strategies, represented by cluster 3, performed the best. This is believed to be a consequence of the volatile and abnormal treasury rates during this phase, which led to attractive investment opportunities. The shifting performance of the different clusters and risk premia investigated shows that diversification and tactical allocation opportunities are possible, insights that are useful for all investors using risk premia strategies in their portfolio.

6.1 Further research

As for further research, an interesting idea would be to study different portfolio allocations when analysing risk premia strategies. How should you construct an investment portfolio depending on which economic phases are expected in the future, drawing upon the results of this study or analysing a different sample? There are many variables that need to be taken into account when considering
portfolio construction that would be interesting to analyse, for instance what type of weighting is appropriate and how do different risk profiles perform during different states of the economy. Another suggestion is to do a similar analysis on a wider range of risk premia strategies. The sample of this study was made up of quite a lot of the more common risk premia strategies like momentum, value and carry, but there are certainly more strategies out there that are not as well known and lack research focus.
7 REFERENCES

7.1 Journals and reports


### 7.2 Electronic sources


Cluster performance in different macroeconomic environments based on an equally weighted allocation. The environments are growth up, growth down, inflation up and inflation down.
Risk-parity allocation

Figure 21. Risk-parity allocation.

Cluster performance in different macroeconomic environments based on an risk-parity allocation. The environments are growth up, growth down, inflation up and inflation down.