Asset Management

Management of Systematic Return Strategies
A Primer

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The image concept symbolizes the robust design of our framework for systematic return strategies and the meticulous analysis that it is based upon. The interlocking gearwheels emphasize the interaction of the various systematic return strategies in the portfolio.
Foreword

Dear Reader

Just as with natural phenomena, rapid changes in financial markets, as well as in the financial industry, are very often hard to explain or comprehend from an equilibrium-centered worldview. Danish theoretical physicist Per Bak identified a simple but successful theory to help improve our understanding of such occurrences. His concept of “self-organized criticality” showed how wild fluctuations arise even in his oversimplified sandpile models.

Armed with this intuition, one cannot expect the real world to follow well-behaved equilibrium dynamics, be it in nature or within financial markets. One consequence, for example, is that a single event can dominate all previous fluctuations. In such an uncertain world, it is therefore better to try to identify robust solutions rather than solutions optimized to address historically observed fluctuations. For several decades, the classic buy-and-hold strategy was one such solution, but a growing number of investors think that this may no longer be an optimal allocation in an age when markets are being driven more by central-bank policy and less by pure fundamentals.

Investors are currently stuck between a rock and a hard place. On the one hand, they do not want to miss out on profit opportunities in today’s low-yield environment, but they equally fear capital losses if markets experience another shock not consistent with an equilibrium-centered worldview. While we accept that the complexities of financial markets are here to stay, investors need to be addressing these concerns with more simplified solutions. Systematic return strategies are a particularly viable option because they extract value from structural return sources that are largely independent of central-bank action. At Credit Suisse, we see very interesting opportunities for investors to build more robust portfolios with the help of systematic return funds.

The numerous research papers that investors have to read nowadays are the direct result of the increasing complexities and changes in our investment industry. What those changes require is a broader perspective away from linear relationships and incorporation of real-world uncertainties into the realm of the investment practitioner.

This report distills some of the most relevant research findings in the field of systematic return strategies. It highlights the practical areas that should be of central concern when it comes to using them within the asset allocation framework of investment professionals. The paper also draws heavily from the day-to-day experience of our Systematic Return team at Credit Suisse Asset Management Switzerland and thus delivers interesting insights for academics and practitioners alike.

We wish you an interesting and entertaining read, and we hope that this report will be useful for your sphere of activity in the financial markets.

Michael Strobaek
Global Chief Investment Officer
& Head Asset Management Switzerland
“We cannot solve our problems with the same thinking we used when we created them.” – Albert Einstein
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Executive Summary

This report contains three sections, all of which can be read independently of one another. At the beginning of each section, a summary page highlights the main points.

1. The Fundamentals of Systematic Return Strategies
In the past, the classic equity/bond mixture within the traditional balanced concept was sufficient to enable many investors to achieve their return targets. The world is changing, however. With interest rates at record lows, investors may not be enjoying the diversification and capital preservation properties of global bonds like they did in the past. So, global bonds are no longer the answer. In search of potential solutions, a number of investors have turned to systematic return strategies. Systematic return strategies are fully transparent, objective and directly investable strategies that aim to monetize risk premia. They consist of a set of trading rules created to capture specific risk premia embedded in traditional and nontraditional asset classes. However, most investments (traditional or systematic return strategies) behave similarly during risk-off periods. Therefore, diversification, which is normally a powerful risk control, leads to unsatisfactory results in market downturns. We address this issue by introducing a simple but robust classification scheme for almost all systematic return strategies, aiming to identify truly diversifying investments.

2. Portfolio Construction Using Systematic Return Strategies
The main benefit of portfolio construction stems from the notion of diversification. The idiosyncratic risk of individual assets can be substantially reduced if the portfolio contains a sufficient number of assets that are not perfectly correlated. So, adding systematic return strategies to a balanced portfolio can increase diversification of the resulting portfolio because these strategies tend to exhibit low correlations to bonds and equities. Portfolio construction often involves some sort of portfolio optimization. Therefore, a risk model and an objective are chosen and inputs need to be estimated. Both the choice of model and the input parameter estimation are subject to errors, which introduces additional risks. These risks can be particularly prominent for systematic return strategies since they often possess only a limited set of live data. We discuss these issues in depth and provide a straightforward, effective solution. Our guiding principle here is that there is a trade-off between the ex-ante optimality and the robustness of the optimization results.

3. Implications for Investors
Systematic return strategies can provide investors with more direct access to the return drivers, and at the same time they can share the liquid tradability and thus the flexibility of traditional asset classes. Furthermore, they can give investors access to a larger opportunity set than traditional investment strategies and can therefore increase diversification when added to an existing portfolio. Another advantage for investors is that these strategies do not require explicit forecasts of returns and risks for asset classes or securities. The methodologies underlying these systematic return strategies rest on publicly available market information. Our proposed robust allocation minimizes the necessity of forecasting individual returns, so investors do not have to rely on forecasting skills. Investors will find systematic return strategies a viable alternative to balanced portfolios during market-correction periods.
1. The Fundamentals of Systematic Return Strategies

Traditional asset classes such as bonds, equities and foreign exchange (FX) go hand in hand with a number of risk premia that are persistent and attached to certain economically well-understood and empirically documented sources of risk. Extracting these risk premia often involves specific methodological, nondiscretionary investment rules known as systematic return strategies.

Systematic return strategies are fully transparent, objective and directly investable. Their aim is to capture specific risk premia embedded in traditional and nontraditional assets. The resulting distinct statistical properties of a strategy’s return can differ substantially from those of the underlying asset classes. Many systematic return strategies show similar behavior in risk-off market situations. Diversification is therefore an issue.

In this section, we study the benefits of systematic return strategies for risk-averse investors. First, we provide an overview of systematic return strategies. Next, we introduce a simple but effective classification scheme that can help investors build “all-weather portfolios” that retain some diversification benefits even during times of crisis. We show that systematic strategies offer unique risk/return characteristics that can help to improve portfolio efficiency. Therefore, we encourage a paradigm shift toward investing in portfolios of systematic strategies as opposed to portfolios of traditional assets.
1.1 Introduction

For many years, investors in balanced portfolios relied on fixed-income markets to provide yield income, diversification and elements of capital protection.

The chart below shows the performance of US equities relative to US government bonds during various crisis episodes. We see that whenever there was a significant equity crisis, the bond market, on average, delivered exactly what investors were expecting of it, i.e. protection.

However, after three decades of prolonged yield compression, many institutional and private investors are concerned about how they will achieve their investment objectives going forward. Unprecedented central-bank action forced investors to move up the risk curve, which in turn depressed yields further and stretched valuations of risky assets. There is now growing evidence that investors are feeling increasingly uncomfortable with the elevated risk levels of the fixed-income holdings in their portfolios. They are particularly concerned about the potential drawdown risks in a rising yield environment.

Looking ahead, the historical trend of fixed-income investments providing downside protection and diversification benefits to balanced portfolios is unlikely to continue to the same extent as before. In short, a simple buy-and-hold strategy when investing in fixed income within balanced portfolios may not work when yields start rising from their multi-decade lows.

There is a growing trend that more and more investors are considering replacing part of their traditional portfolio allocations with income solutions that make greater use of investing in uncorrelated risk premia. According to Kaya et al. (2012), the idea of risk premium investing has received a lot of attention, especially after the last financial crisis, when an increasing number of investors focused on risk classes rather than asset classes. Extracting these risk premia often involves nondiscretionary investment rules, which we call systematic return strategies.

Figure 1: Equities and Bonds during Crisis Time

Source: Datastream, own calculations. Both indices are not directly investable. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.
1.2 Definition

A systematic return strategy is an investment strategy that invests according to transparent, predefined nondiscretionary rules based on public information available at the time of investment. For a long-only investment in a certain stock, such a rule could be very simple: invest all capital in this one stock and never change. The rules for long-only investments in an equity index (for example through exchange-traded funds) would be more complicated. Usually, stocks are added or excluded from an index according to market capitalization and many other criteria defined in the index rules.

The index rules are predefined, but input variables like the market capitalization of each stock in the universe cannot be known in advance.

An investment in an active fund would not necessarily be considered a systematic return strategy since one does not know what a fund manager will do given a certain set of information. In other words, the rules are not predefined.

Investing is about taking risks. It is a well-established paradigm in finance that every investment that is expected to deliver an excess return above the risk-free rate has to be exposed to some additional risks. The expected excess return over the risk-free rate is known as the risk premium. Risk premia are usually not directly (individually) tradable but can be monetized via systematic return strategies. Returns from systematic strategies are expected to reflect the respective risk premia but are affected by market fluctuations. This means that return realizations can turn out to be negative, depending on the time period investigated.

Risk-averse investors typically construct portfolios with a positive aggregated risk premium, i.e. they expect an excess return above the risk-free rate for bearing additional risks. There are different ways for investors to look at risk premia:

- One can define a risk premium based on the type of investment. For example, the expected excess return of equities is called the equity risk premium.\(^1\)
- One can define risk premia based on the source of risk. In this case, the equity risk premium could be viewed as a combination of a business risk premium, a recession risk premium, a liquidity risk premium, a country-specific risk premium and potentially many more.
- Statistical methods like principal component analysis (PCA) can be used to separate and isolate different "abstract" risk premia for an investment.

No matter which way one dissects risk premia, the requirements from a practical portfolio management point of view are:

- Risk premia should be investable.
- A larger number of sustainable positive risk premia is preferable (all else equal).
- More economically and statistically independent risk premia are better (all else equal).

Traditional asset classes such as equities, bonds, foreign exchange, commodities and their derivatives can be considered baskets of risk premia. The allocation of these baskets of risk premia is, in general, not optimal.

With the help of systematic return strategies, it is possible to gain more direct access to less correlated risk premia. In Figure 2, we show this for some sample systematic strategies\(^2\) and a typical portfolio of traditional assets.\(^3\)

We can see that the average correlations are significantly lower for the strategies compared to those for the traditional assets. Moreover, the average correlations are more stable as well. This was particularly significant during the collapse of Lehman Brothers in 2008, when the average correlations of traditional assets spiked and remained at high levels for several years, while the correlations of systematic strategies remained virtually unchanged.

![Figure 2: Average Two-Year Correlations of Some Systematic Return Strategies Compared to Investments in Sample Traditional Assets](image)

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\(^1\) The notion of risk premia is closely related to the famous capital asset pricing model (CAPM), where only one risk factor, namely the market beta, is considered. This model was subsequently extended by Fama, French and Sharpe to multiple premia.

\(^2\) Systematic return strategies included were: CBOE S&P 500 PutWrite Index, S&P 500 Pure Value Total Return Index minus S&P 500 Total Return Index, MSCI World Small Cap Index minus MSCI World Large Cap Index, UBS American Volatility Arbitrage Index, BofA Merrill Lynch US High Yield Index minus BofA Merrill Lynch US Corporate Index, J.P. Morgan G10 FX Carry Index, Barclay Systematic Traders Index.

\(^3\) For traditional assets we have chosen the S&P 500 Index, S&P GSCI Excess Return Index, Barclays GlobalAgg Total Return Index, Dollar Index, DAX Index, SMI Index, MSCI Total Return Emerging Markets Index, Nikkei Index, EURO STOXX 50 Index.

Source: Bloomberg L.P., own calculations. As from 30.11.2001 to 29.08.2014, based on monthly data. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.
On average, systematic return strategies are less correlated among each other than traditional asset classes, which can improve portfolio diversification. Since systematic strategies can target individual risk premia more directly, they enable portfolio managers to come closer to an optimal portfolio. Therefore, we argue that systematic strategies using simple quantitative investment rules based on straightforward economic reasoning are better portfolio building blocks than traditional asset classes. Extracting risk premia with systematic investment strategies is a very well-established and documented concept among investment professionals, and it can be found in all asset classes. To provide a better and more practical understanding of systematic return strategies, we list a few common ones along with their most important risk premia in the table below.

### Table 1: Illustrative Examples of Risk Premia in Various Asset Classes

<table>
<thead>
<tr>
<th>Asset Classes</th>
<th>Examples of Systematic Return Strategies</th>
<th>Risk Premia (Examples)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Equity</strong></td>
<td>- Value stocks versus benchmark</td>
<td>- Value risk premium</td>
</tr>
<tr>
<td></td>
<td>- Small-cap stocks versus benchmark</td>
<td>- Small-cap risk premium</td>
</tr>
<tr>
<td></td>
<td>- High-dividend versus low-dividend stocks</td>
<td>- Dividend risk premium</td>
</tr>
<tr>
<td></td>
<td>- Covered put writing/covered call writing</td>
<td>- Equity-protection risk premium</td>
</tr>
<tr>
<td></td>
<td>- Calendar effects in equity indices</td>
<td>- Equity-risk premium</td>
</tr>
<tr>
<td></td>
<td>- Merger arbitrage</td>
<td>- Liquidity and deal risk premium</td>
</tr>
<tr>
<td></td>
<td>- Volatility arbitrage</td>
<td>- Equity-volatility risk premium</td>
</tr>
<tr>
<td><strong>Fixed Income</strong></td>
<td>- High-yield versus investment-grade bonds</td>
<td>- Default risk premium</td>
</tr>
<tr>
<td></td>
<td>- New on-the-run issues versus off-the-run bonds</td>
<td>- Liquidity risk premium</td>
</tr>
<tr>
<td></td>
<td>- Convertible bond optionality versus listed options</td>
<td>- Volatility and liquidity risk premium</td>
</tr>
<tr>
<td><strong>Currencies</strong></td>
<td>- High-yielding currencies versus low-yielding FX</td>
<td>- Liquidity and inflation risk premium</td>
</tr>
<tr>
<td></td>
<td>- FX-implied versus realized volatility spread</td>
<td>- Currency-volatility risk premium</td>
</tr>
<tr>
<td><strong>Commodities</strong></td>
<td>- Preroll commodity indices versus benchmark</td>
<td>- Index-liquidity risk premium</td>
</tr>
<tr>
<td></td>
<td>- Deferred indices versus benchmark</td>
<td>- Supply/demand risk premium</td>
</tr>
<tr>
<td></td>
<td>- Implied versus realized commodity volatility</td>
<td>- Commodity-volatility risk premium</td>
</tr>
<tr>
<td></td>
<td>- Backwardated versus contangoed commodities</td>
<td>- Inventory risk premium</td>
</tr>
</tbody>
</table>

Source: Credit Suisse AG.

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4 In a traditional balanced portfolio of equities and bonds, it can be a challenge to reduce exposure to rising interest rates or rising equity volatility, for example, without causing many other (sometimes unintended) changes to other risk factors in the portfolio.
The difference between systematic return strategies and other quantitative strategies or strategies based on technical analysis is mainly an ideological one: when investing in systematic return strategies based on risk premia, investors expect to be compensated for certain risks that they are willing to bear. Our philosophy is that a well-diversified portfolio of systematic return strategies makes it possible to better diversify those risks compared to a portfolio of traditional asset classes. We do not believe that superior forecasting or information-processing abilities are the driver of performance without additional risks, as may be suggested by some strategies based on quantitative or technical analysis.

Since systematic return strategies rest on historical market information and do not require any kind of return or risk forecasts, they could be interpreted as being mainly passive strategies. However, the investor still has to make an active decision when he or she selects a strategy from the overall universe of available strategies. What is the exposure, how do the strategies behave during risk-off markets, and do they overlap in terms of tail-risk behavior? Those are just some of the questions that need to be answered within the context of an investment process for a portfolio of systematic return strategies.

1.3 A Simple Classification Scheme for Systematic Return Strategies

To help answer those questions, we introduce a simple classification scheme for systematic return strategies. This particularly presents a challenge because in the field of systematic return strategies, there is no commonly agreed upon scientific terminology yet. The classification scheme has three main purposes: to organize the strategies we deal with, to see how strategies are related to each other, and to evaluate the appropriateness of new strategies. Besides the simplicity of our classification scheme that uses only two categories, we assert that it can be a powerful tool for understanding diversification, especially in extreme market environments.

Explaning the nature of investment strategies has been a major topic of academic literature. Sharpe (1992), for example, showed that returns from strategies employed by mutual funds in the US were highly correlated with standard asset classes, and that the performance differences of these strategies could be explained by different styles or asset class exposures. Other authors expanded Sharpe’s model by adding additional factors in order to analyze the investment strategies of hedge funds. However, many questions remain open. Given the theoretically unlimited universe of possible strategies, not all of them can be captured by the style factors of the authors. In addition, very often there is not enough empirical data available to draw the correct conclusion about the factor exposure of systematic strategies. The nonlinear relationship between “style factors” and the corresponding asset classes is not always so easily captured. Our classification scheme therefore goes beyond the classical (linear) factor model approach. It is motivated by the idea that systematic strategies should be interpreted as a derivative of traditional asset classes due to their option-type payoffs (Perold and Sharpe 1988).

We use a taxonomy that applies specific criteria to distinguish between two categories: “carry” and “trend-following.” Carry strategies provide income in stable market environments, whereas trend-following strategies aim to act as a return diversifier, especially amid unstable market environments.

The idea is quite simple. Although we acknowledge that our classification scheme is a simplification of the real world, we believe that our approach can help absolute-return investors to better allocate strategies in a market where exposure to tail risk cannot be diversified away.

Carry Strategies

The first of our categories is carry strategies. Here, strategies are classified based on their nonlinear behavior toward the broader market, with a particular focus on negative market returns.

Typically, the carry of an asset is the return obtained from holding it. A classic example is high-yield bonds, where investors can collect income from coupon payments as compensation for issuer default risk. Carry strategies – sometimes also called relative value strategies – are also used to extract a risk premium by holding two offsetting positions in similar instruments or asset classes where one of the positions creates a price return or cash flow that is greater than the obligations of the other. An example of such a strategy would be going long high-yield bonds and, at the same time, short government bonds to extract a default risk premium.

Many risk premium strategies that are commonly classified as carry, income or relative value strategies can be seen as compensation for investors for assuming some form of systematic risk. In such cases, the investment provides insurance against systematic risks. Such risk premium strategies have risk profiles that are similar to put-selling strategies (selling direct insurance against price risks).

The common characteristic of carry strategies is that they have a positive expected return. However, during sharp market corrections, these strategies can suffer as well. Similarly, selling out-of-the-money puts gives investors the right to sell stocks at a price below the current level. Selling puts is usually profitable in rising or range-bound markets, but can become very loss-making if equity prices move sharply lower and volatility rises significantly.

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5 In some cases, the size of the risk premia is also attributed to what market participants consider to be some kind of “market inefficiency.” In recent years, a number of articles have suggested that these “inefficiencies” can be traced back to behavioral bias or structural imbalances. Please refer to Appendix 3 for further elaboration.

6 The insurance premium is particularly high for short-dated volatility, which is due to the well-known phenomenon in option markets that short-dated options trade very rich in terms of implied volatility, since the nonhedgeable jump risk plays a decisive role here.
How can we evaluate the generic risk behavior of carry strategies? From option pricing theory we know that the delta is the first derivative of the option price in response to market changes. As the underlying market moves, the option price is not likely to change in the same fashion, but instead changes over some curved function. The delta of the option position – and in our case the delta of the strategy – can therefore only be a first linear approximation of the price change in the systematic return strategy when there is a small change in the underlying market factor. In order to capture more of the dynamics of the systematic trading strategies, we have to go farther and look for the convexity of the strategy. Convexity is a measure of the sensitivity of the delta of an option – in our case the delta of the strategy – to changes in the underlying.7

The risk behavior of systematic return strategies can be approximated as a function of equity returns. We consider carry strategies to be negative convexity strategies: covered call or put writing, going long equities with certain stop-loss rules, corporate bonds, high-yield bonds, emerging-market bonds, relative value, equity long/short strategies and certain portfolio construction and rebalancing techniques all fall into this category.8

If the dependence on the equity market is concave (negative convexity), then we put the strategy in the carry category.

Popular strategies capitalizing on monetizing the insurance premium via option writing include the covered-call strategy and the aforementioned put-writing strategy. The tracked and independently calculated CBOE S&P 500 PutWrite Index is an example of the latter strategy. The CBOE S&P 500 PutWrite Index measures the performance of a hypothetical portfolio that sells S&P 500 put options against a cash reserve. The index rules determine the number of options to sell each month, their strike price and their maturity, and accordingly are independent of the views of an investment manager.

The issue many investors are facing is that selling insurance suggests low risk when applying standard metrics such as the Sharpe ratio or alpha, for example. However, many practitioners and researchers argue that this standard approach gives too narrow a perspective in that it does not fully reflect the true risk content of all the different risk premia that are related with this strategy.

![Figure 3: Performance of CBOE S&P 500 PutWrite Index versus S&P 500 Total Return Index](source)

When we look at Figure 4, we see from the return distribution that the CBOE S&P 500 PutWrite Index returns show a much lower skewness and considerably higher kurtosis compared to the S&P 500 Total Return Index.9 Skewness is a measure that indicates that the tail on one side of the distribution is longer than the other (i.e. the distribution is asymmetrical). The fourth standardized moment is kurtosis, which is an indicator for distributions with more extreme deviations from the mean (e.g. infrequent but very large losses) than would be expected by a normal distribution with the same variance.

Even though the beta of the CBOE S&P 500 PutWrite Index is lower than one, it still outperforms the market, contradicting the Efficient Market Hypothesis (EMH), which is usually attributed to alpha.10

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7 The price process of the option is said to be convex in the underlying if the second derivative with respect to the price of the underlying is positive.
8 By applying this logic, it should not come as a surprise that we also classify momentum portfolios that go long past winners and short past losers in the equity markets as negative convexity trades. Momentum and trend-following often seem similar strategies, but in reality they are not because they exhibit very different empirical behaviors. This assertion is corroborated by studies by Daniel et al. (2012) and Avramov et al. (2014), which found that the empirical return distribution of a momentum portfolio between 1927 and 2010 has both strong excess kurtosis and strong negative skewness.
9 The Jarque-Bera test for normality shows a value of $17 \times 10^3$ for the CBOE S&P 500 PutWrite Index strategy, whereas the critical value is 5.99 at the 95% significance level.
10 As introduced in the CAPM framework.
Table 2: Return Statistics of the S&P 500 Total Return Index and the CBOE S&P 500 PutWrite Index

<table>
<thead>
<tr>
<th>Statistics</th>
<th>S&amp;P 500 Total Return Index</th>
<th>CBOE S&amp;P 500 PutWrite Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Return</td>
<td>109.4%</td>
<td>187.5%</td>
</tr>
<tr>
<td>Return p.a.</td>
<td>4.8%</td>
<td>7.0%</td>
</tr>
<tr>
<td>Volatility</td>
<td>18.5%</td>
<td>12.4%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.35</td>
<td>0.61</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.51</td>
<td>-2.49</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>5.37</td>
<td>22.91</td>
</tr>
<tr>
<td>Maximum Drawdown</td>
<td>54.7%</td>
<td>36.4%</td>
</tr>
</tbody>
</table>

Source: Bloomberg L.P., own calculations. Weekly data as from 29.01.1999 to 29.08.2014. Both indices are not directly investable. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.
In many popular market models (see, for example, Fang and Lai 1997), skewness and the kurtosis are dedicated risk factors, and the superior performance of the CBOE S&P 500 PutWrite Index could be partly explained in this model with the exposure to unfavorable higher moments of the return distribution. The CBOE S&P 500 PutWrite Index has a different skewness than that of the S&P 500 Total Return Index. This can be explained by the fact that short put options have a first-order sensitivity to moves in the underlying (delta) between 0% and 100%, whereas at-the-money forward (ATMF) options have a sensitivity of around 50%. As the market drops, the first-order sensitivity (delta) increases, and as the market rises the delta decreases. This explains the asymmetry of the return distribution. The maximum drawdown of the CBOE S&P 500 PutWrite Index stands at 36.4%, compared to 56.2% for the equity index. This is due to the fact that options have a delta of less than 100%, and at each monthly option rebalancing the delta is set back to approximately 50% while at the same time locking in gains from monetizing option premia, which can cushion potential earlier losses.

Therefore, it can be seen from the CBOE S&P 500 PutWrite Index example that by gaining exposure to new sources of risk in a systematic way, the traditional risk-adjusted performance on the surface looks superior when compared to the underlying market. In our example, the Sharpe ratio for the CBOE S&P 500 PutWrite Index is more than twice that of the S&P 500 Total Return Index (Table 2). This figure looks so impressive that it is tempting to invest all of one’s assets in such a systematic return strategy.

However, attributing the outperformance of put writing to alpha might be misleading because it might derive from exposure to higher-order risks that an underspecified model will not be able to address.

The example of systematic put writing shows that systematic return strategies can have exposure to higher-order risks.\textsuperscript{11,12} Let us illustrate this for some carry strategies. In Figure 5, we have plotted the empirical functional dependencies of six exemplary carry strategies with respect to the broad equity market index (we are using the S&P 500 Total Return Index as a proxy for equity market risk).

\textsuperscript{11} Another example is the well-known merger arbitrage strategy. Here, one goes long in shares of the target company after a deal is announced and holds them until completion or termination of the deal and, at the same time, hedges the portfolio of target-company shares with shares of the acquirer or with the equity market (to make the strategy beta-neutral). The objective is to capture the difference between the acquisition price and the target’s stock price before completion of the merger. The performance of this strategy is positively correlated with market returns in severely falling markets, but uncorrelated in flat or rising markets. When risk aversion increases across the board, credit conditions deteriorate and merger deals thus tend to fail. Mitchell and Pulvino (2001) interpret the returns of the merger arbitrage strategy as similar to those obtained from selling uncovered index put options because they show a nonlinear relationship with market returns. In essence, the authors found that excess returns can be interpreted as a compensation for providing liquidity, especially in negative market regimes. Och and Pulvino (2004) show that this strategy can be seen as selling insurance to shareholders against the risk that the deal may fail.

\textsuperscript{12} Many popular carry strategies in the fixed-income space can be characterized as synthetic option positions, as Fung and Hsieh (2002) show.
The first strategy is the CBOE S&P 500 PutWrite Index that we have already discussed. This strategy collects premium income by monetizing the volatility risk premium options’ implied volatility. The second strategy is a combination of a long position in the S&P 500 Pure Value Total Return Index and a short position in the S&P 500 Total Return Index. This strategy benefits from the value risk premia in the equity markets. The third strategy shows a combination of a long position in the MSCI World Small Cap Index and a short position in the MSCI World Large Cap Index. Here, the goal is to benefit from the small-cap risk premia in equity markets.

13 We have used this method because it fits smooth curves to local subsets of the empirical data and thus does not require specification of a global function to fit the data set. The dark blue line fits 85% of the data and disregards data points where absolute market returns are extreme. The light blue line fits the entire data set. We chose to highlight the center portion because the tails only contain few data points and the explanatory power decreases markedly.
The fourth strategy is the UBS American Volatility Arbitrage Index. This strategy consists of short exposure to one-month variance swaps on the S&P 500 Total Return Index, with the aim of monetizing the spread between the implied and realized volatility of the S&P 500 Total Return Index constituents (volatility risk premium). The fifth strategy is a long position in the Bank of America Merrill Lynch 1- to 10-year US High-Yield Index and a short position in the Bank of America Merrill Lynch 1- to 10-year US Corporate & Government Bond Index, which aims to monetize the liquidity and default risk premia of high-yield bonds.14

Finally, the J.P. Morgan G10 FX Carry strategy aims to exploit the empirically observed fact that currencies with comparatively higher interest rates do not tend to depreciate (as implied by currency forwards) by selecting four G10 currency pairs based on interest-rate differentials on a monthly basis.15

Table 3: Statistics for Six Systematic Return Strategies

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Return</td>
<td>144.5%</td>
<td>196.7%</td>
<td>164.6%</td>
<td>106.7%</td>
<td>35.9%</td>
<td>65.3%</td>
</tr>
<tr>
<td>Return p.a.</td>
<td>6.3%</td>
<td>7.7%</td>
<td>6.9%</td>
<td>5.1%</td>
<td>2.1%</td>
<td>3.5%</td>
</tr>
<tr>
<td>Volatility</td>
<td>11.4%</td>
<td>13.2%</td>
<td>8.2%</td>
<td>8.3%</td>
<td>9.6%</td>
<td>9.3%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.59</td>
<td>0.63</td>
<td>0.86</td>
<td>0.64</td>
<td>0.27</td>
<td>0.42</td>
</tr>
<tr>
<td>Skewness</td>
<td>-1.80</td>
<td>0.86</td>
<td>0.07</td>
<td>-4.27</td>
<td>-1.19</td>
<td>-1.19</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>7.36</td>
<td>6.60</td>
<td>3.39</td>
<td>28.28</td>
<td>6.87</td>
<td>5.71</td>
</tr>
<tr>
<td>Maximum Drawdown</td>
<td>32.7%</td>
<td>38.7%</td>
<td>17.4%</td>
<td>31.5%</td>
<td>37.2%</td>
<td>34.6%</td>
</tr>
</tbody>
</table>

Source: Bloomberg L.P., own calculations. Monthly data as from 31.12.1999 to 29.08.2014. Indices are not directly investable. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.

When looking at the relationship between our sample strategies and the S&P 500 Total Return Index as a proxy for market risk in Table 3, we can make three observations. First, the common feature of these strategies is the fact that the investor should expect to earn a positive return (positive carry) from holding the positions in the longer run, as evidenced by the positive annualized return for all of the strategies. Second, the relationship shows negative convexity, indicated by higher negative skewness in the return distribution for most of the carry strategies. In the case of a falling S&P 500 Total Return Index, the sensitivity, or the delta, to the market increases drastically. In this case, the short put is “in the money” and the position is accumulating losses.15

The income from monetizing the risk premium is overcompensated by mark-to-market losses from the underlying price movement. This has serious consequences for absolute-return investors. Having a portfolio of 30 carry strategies diversified across asset classes means that the portfolio is still not properly diversified since it shows concentrated tail-risk exposure. Third, the dispersion in the scatterplot around the LOESS fit in Figure 5 is an indication that there are other explanatory factors besides the underlying price. These additional factors provide even more diversification potential for an investor than a simple replication would suggest.

14 The spread duration was roughly 3.5 years for the High-Yield Index versus around 3.9 years for the Corporate & Government Bond Index as of the end of March 2014.

15 Taleb (1997), Brunnermeier et al. (2008), Melvin and Taylor (2009) and Menkhoff et al. (2012) discuss the behavior of carry trades’ dynamic trading strategies and analyze their exposure to crash risk.
Using the delta and convexity together gives a better approximation of the change in the strategy value given a change in the market than using delta alone.\textsuperscript{16} However, for professional risk management purposes, this is not sufficient because they ignore the sensitivity of the portfolio to other dynamic features (especially to volatility).\textsuperscript{17}

**Trend-Following Strategies**

Trend-following strategies form the second category in our classification scheme. Almost 200 years ago, the British economist David Ricardo (1772–1823) phrased the golden rules of investing as: “Cut short your losses” and “Let your profits run on” or, in other words, “The trend is your friend.” In rising markets, Ricardo suggested investing more, while recommending exiting or changing sides in falling markets.

Investors who follow this advice do so by going long in rising markets or short in falling markets in the anticipation that those trends will continue into the future.\textsuperscript{18} A large body of empirical literature has been published over the last decades to support the notion that segments of financial markets do indeed trend over identifiable periods.\textsuperscript{19} The empirical justification for these types of strategies is based on the existence of significant autocorrelation in the asset return’s time series (see, for example, Lo and MacKinlay 1990). The existence of these trends can often be traced to some behavioral patterns.

This includes an initial underreaction and then a delayed overreaction compared to the classical rational investor with unlimited resources and unconstrained borrowing capabilities as the main explanations for its existence.

An example of “overreaction” is the decision by investors to cut losses after an asset portfolio has dropped to a critical value. With unchanged liabilities, the leverage then increases, which could threaten the survival of the business. When more investors are forced to cut back on losses, this can initiate a positive feedback mechanism that can drive prices lower, thus causing more investors to sell assets, which in turn depresses prices further. This is a classic situation where, for example, value stocks can become even more valuable.

Trend-followers believe that prices tend to move persistently upward or downward over time. When a trend-follower expects autocorrelation in returns, he follows the strategy “Buy high, buy higher or sell short and sell shorter.” Typically, this kind of autocorrelation in returns can best be monetized during larger market moves in either direction. During quiet periods, returns tend to be rather small and may even be negative.

\textsuperscript{16} In general, the larger the move in the underlying, the larger the error term of a linear approximation.

\textsuperscript{17} A thorough discussion is beyond the scope of this report. Interested readers are recommended to consult the relevant literature (see, for example, Taleb 1997).

\textsuperscript{18} Trend-following strategies operate by using rules such as moving averages or moving average crossovers or other more complex approaches to signal when to buy or sell based on underlying trends.

\textsuperscript{19} See Moskowitz et al. (2012) for a comprehensive analysis – the authors find a significant time series momentum effect that is consistent across S8 equity, currency, commodity and bond futures over a time span of 25 years. Miffre and Rallis (2007), Menkhoff et al. (2012), Moskowitz et al. (2012) and, more recently, Hutchinson and O’Brien (2014) provide further evidence of the consistently high long-term performance of trend-following strategies.

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**Figure 6: Performance of Barclay Systematic Traders Index versus S&P 500 Total Return Index**

![Figure 6: Performance of Barclay Systematic Traders Index versus S&P 500 Total Return Index](source: Bloomberg L.P. Monthly data as from 31.01.1999 to 29.08.2014. Both indices are not directly investable. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.)
A widely accepted benchmark index for measuring the performance of trend-following strategies is the Barclay Systematic Traders Index. The index represents an equally weighted composite of managed programs whose approach is at least 95% systematic. At the start of 2014, there were 482 systematic programs included in the index. Figure 6 compares the S&P 500 Total Return Index to the Barclay Systematic Traders Index for the period from 31.01.1999 to 29.08.2014. Obviously this is not a fair comparison since the S&P 500 Total Return Index is a basket of 500 liquid stocks, whereas systematic programs can typically diversify across a larger number of liquid assets in different markets.

This, in part, explains why the returns of the Barclay Systematic Traders Index are less erratic than the returns of the equity index. Therefore, the risk/return relationship as measured by the Sharpe ratio is higher for the systematic strategy. Both the total return and the volatility are lower for the Barclay Systematic Traders Index compared to the S&P 500 Total Return Index. However, the reduction in volatility by almost 50% leads to significantly higher risk-adjusted returns.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>S&amp;P 500 Total Return Index</th>
<th>Barclay Systematic Traders Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Return</td>
<td>109.4%</td>
<td>78.9%</td>
</tr>
<tr>
<td>Return p.a.</td>
<td>4.9%</td>
<td>3.8%</td>
</tr>
<tr>
<td>Volatility</td>
<td>15.3%</td>
<td>8.1%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.39</td>
<td>0.50</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.56</td>
<td>0.29</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>0.90</td>
<td>0.51</td>
</tr>
<tr>
<td>Maximum Drawdown</td>
<td>50.9%</td>
<td>11.8%</td>
</tr>
</tbody>
</table>

Source: Bloomberg L.P., own calculations. Monthly data as from 31.01.1999 to 29.08.2014. Both indices are not directly investable. Without costs or fees. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.

The index reports monthly returns only, which can hide the true volatility of returns. This smoothing effect of monthly returns can lead to an upward bias in performance measures. For more details, see, for example, Huang et al. (2009).
The advantage of investing in trend-following strategies is demonstrated when combined with traditional assets and many other popular systematic return strategies. When this is done, trend-following strategies show interesting risk-mitigation properties in times of market stress. In fact, according to Ilmanen (2011), trend-following strategies perform well during periods of sharp equity-market corrections and rising volatility. They have therefore been very good diversifiers for risky assets. This can be confirmed when we compare the price behavior of the Barclay Systematic Traders Index with that of the S&P 500 Total Return Index during past crisis periods (see Figure 7).

Fung and Hsieh (2001) and Fung and Hsieh (2002) use a portfolio of options to model the nonlinear payoff from trend-following strategies. Other authors interpret trend-following strategies as an approximation of a long-straddle position (a combination of a long call and a long put position) because the strategy gains from large underlying market movements in either direction. From option theory, we know that long option positions exhibit positive convexity. This is because a long option position can only lose the premium (with, theoretically, unlimited gain potential), whereas a short position, in theory, can incur unlimited losses.

Accordingly, we classify any systematic trading strategy that resembles a payout with positive convexity (long optionality) as a trend-following strategy.

In Table 5, we have summarized the return statistics of three exemplary positive convexity strategies: the S&P 500 VIX Short-Term Futures Index, the S&P 500 VIX Futures Tail Risk Index and the Barclay Systematic Traders Index.

The negative return for the S&P 500 VIX Short-Term Futures Index and the S&P 500 VIX Futures Tail Risk Index appears to be the price that an investor has to pay for the asymmetry (positive convexity or skewness of the return distribution) of the two strategies. Although the skewness of the return distribution is positive and high, the investor has not gained anything from this tail-risk insurance when we look at the total return numbers. The investor had to pay a high price for gaining exposure to positive convexity. On the other hand, the Barclay Systematic Traders Index has a higher annualized return and a lower skewness. The index itself is a diversified basket of strategies (across instruments and markets). Underlying trend-following programs apply various risk management and money management techniques, which themselves can be a source of positive convexity.

In Figure 8, we show the return distributions of these strategies and the functional dependence with respect to a broad equity market. The local regression shows positive convexity for the center of the market returns.

The local regression shows that there is an imperfect fit to the empirical data because other factors still play a role that may not be neglected. In general, this can be viewed as positive for the investor because those additional parameters can have additional diversification benefits.

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21 See Ilmanen (2011). He emphasizes that trend-following benefits from changes in realized volatility and not from market-implied volatility.

22 For more information, see http://us.spindices.com. The index aims to have a constant one-month rolling long position in the first two VIX futures contracts. This means that the strategy benefits from an increase in the VIX. However, depending on the shape of the VIX futures curve, rebalancing can create negative roll yield.

23 The S&P 500 VIX Futures Tail Risk Index provides long volatility exposure. The index tries to mitigate the negative impact of roll yield via a rebalanced short exposure. See http://us.spindices.com for more information.
For the VIX futures strategies, the excess return index is used because it is often used as an overlay in an unfunded format. Total return is excess return plus the yield on short-term liquidity (often the three-month federal funds rate is used).

When comparing Table 5 and Figure 8, we see that trend-following and carry strategies can have complementary risk/return profiles that argue in favor of our classification scheme. We believe that its main advantage is that it helps investors with an absolute-return objective not to overestimate the diversification effects in their portfolios during crisis periods. By explicitly focusing on the risk-off behavior, we purposely disregard many other properties that may be important in normal markets but might diminish in times of crisis.

### Table 5: Return Statistics for Alternative Trend-Following Strategies

<table>
<thead>
<tr>
<th>Statistics</th>
<th>S&amp;P 500 VIX Short-Term Futures Index</th>
<th>S&amp;P 500 VIX Futures Tail Risk Index</th>
<th>Barclay Systematic Traders Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Return</td>
<td>-99.3%</td>
<td>-14.6%</td>
<td>26.9%</td>
</tr>
<tr>
<td>Return p.a.</td>
<td>-43.8%</td>
<td>-1.8%</td>
<td>2.8%</td>
</tr>
<tr>
<td>Volatility</td>
<td>70.4%</td>
<td>61.9%</td>
<td>6.5%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>-0.51</td>
<td>0.15</td>
<td>0.45</td>
</tr>
<tr>
<td>Skewness</td>
<td>2.62</td>
<td>7.46</td>
<td>0.44</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>11.89</td>
<td>66.28</td>
<td>0.32</td>
</tr>
<tr>
<td>Maximum Drawdown</td>
<td>99.6%</td>
<td>72.7%</td>
<td>11.8%</td>
</tr>
</tbody>
</table>

Source: Bloomberg L.P., own calculations. As from 31.12.2005 to 29.08.2014. Indices are not directly investable. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.

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34 For the VIX futures strategies, the excess return index is used because it is often used as an overlay in an unfunded format. Total return is excess return plus the yield on short-term liquidity (often the three-month federal funds rate is used).
LOESS is also known as locally weighted scatterplot smoothing (LOWESS). This robust version of LOESS assigns zero weight to data outside six mean absolute deviations. Here we used the robust LOESS with a span of 60%.

Source: Bloomberg L.P. Monthly data as from 31.12.1999 to 29.08.2014. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.

\footnote{LOESS is also known as locally weighted scatterplot smoothing (LOWESS). This robust version of LOESS assigns zero weight to data outside six mean absolute deviations. Here we used the robust LOESS with a span of 60%.}
2. Portfolio Construction Using Systematic Return Strategies

Many investors are not fully free in their investment approach. This becomes apparent especially during crisis periods. Although it seems to be a rational intention to limit losses during crisis periods, if too many market participants are forced to do this at the same time (e.g. due to regulatory constraints), this can create a feedback loop in the system with very negative consequences. Portfolios once considered optimal will turn out to be less resilient to systemic shocks. So, what investors ultimately are looking for are robust portfolios that can cope better with shocks in the market.

In this section, we analyze how a smart combination of trend-following and carry strategies can make portfolios more robust. In addition, we introduce some guiding principles for selecting the most appropriate systematic return strategies. We then analyze innovative portfolio construction methods for systematic strategies with a focus on associated estimation and assumption risks. We additionally illustrate how these risks can have adverse impacts on the out-of-sample performance of optimized portfolios. We discuss portfolio construction methods that take these risks into account and can lead to a more robust allocation. As a particularly simple and straightforward method, we present the constrained entropy approach, which leads to less concentrated and more robust portfolios. The aim is to show how this approach can deliver superior out-of-sample risk-adjusted performance, which is relevant for both relative-return and absolute-return investors.
2.1 The Role of Systematic Return Strategies in Institutional Portfolios

In theory, institutional investors such as insurance companies or pension funds are thought to have a long-term investment horizon and, in turn, a higher tolerance for short-term market fluctuations. In reality, though, institutional investors have shorter-term performance reporting requirements and regulatory capital constraints for their shareholders, clients and regulators. All of these factors can lead to procyclical investment behavior. This is especially true during general market declines because preservation of capital is a priority in order for retirees to cover their living expenses. Also, the time that they can wait for the market to recover the losses is limited. The larger the drawdowns, the more difficult it becomes for the investor to break even to previous levels. So, for example, an investment that loses 20% requires a gain of 25% to break even, and a loss of 50% requires 100%. With a loss of 100%, the entire portfolio is wiped out and business has thus ended.

Withdrawals driven by the need for capital preservation can become a vicious circle for institutional investors. Market losses can lead to client redemptions, which in turn can lead to further asset price declines due to forced unwinding of portfolio positions in markets with reduced liquidity. This can then lead to even more redemptions. These client redemptions ultimately have the same effect as a margin call, which typically comes at the worst time and prevents the investment manager from participating in any subsequent recovery to the full extent after he was stopped. Hence, we can interpret the position of the institutional investor as a writer of a down-and-out American barrier option with a rebate and negative interest rate.26

The strike price of the barrier option puts a floor under performance and can restrict the investment manager from participating in investments that may look attractive. However, since such an investment may potentially entail short-term losses, the investment manager may become more risk-averse and thus focus on capital preservation to increase his survival probability. One risk measure closely related to the idea of capital preservation is drawdown. Drawdown answers the question: “What would my losses have been if I had entered the market at the worst possible time?”27

In Figure 9, we see on the left-hand side the historical drawdown of the S&P 500 Total Return Index (percentage price decline from the recent high to the current value). On the right-hand side we see the subsequent drawup (percentage price increase from the current value to the subsequent high of the remaining period). We can see that steep drawdowns are typically followed by sharp recoveries.

Therefore, an investor who was stopped either by risk management policies or his or her own drawdown aversion will underperform a benchmark investor who is continuously invested.

26 See Ekström and Wannström (2000). A down-and-out put option (also known as a knock-out put) works like an ordinary put option unless the barrier is breached during the term of the contract, otherwise the option expires worthless.

27 Drawdowns can reveal how successive price drops culminate in a persistent process that cannot be captured by standard risk measures such as variance of returns.
Typically, investors try to avoid drawdowns by simply cutting back on risks with the aim of increasing their short-term survival probability. Over the longer term, however, this is not a real option for the majority of institutional and private investors because, for instance, the liability side might be growing at a constant rate. This may be a guaranteed interest rate with insurance companies or the inflation rate that a private investor wants to keep up with. Therefore, an investment strategy that is primarily based on avoiding risk cannot be an ideal long-term solution.

Positive portfolio convexity can help investors to stick to their investments even in times of increased market stress, and can prevent them from missing market opportunities that are typically most attractive during those periods. However, in the absence of market-forecasting abilities, the investor has to be careful not to overpay for positive convexity.

In the following example, we will illustrate how a combination of carry and trend-following strategies can significantly reduce the risk of a higher portfolio drawdown without running the risk of being stopped out. This is possible by means of the adaptive "cushioning effect" provided by trend-following strategies.

Let us consider two systematic return strategies (the CBOE S&P 500 PutWrite Index and the Barclay Systematic Traders Index) combined in an equally weighted portfolio. The resulting portfolio in Figure 10 can be decomposed into (ignoring transaction costs and fees):

- a cash position and a short put on the S&P 500 Total Return Index; and
- a long put option on the broad market (tail-risk insurance) plus a long call option on the broad market (uncapped upside potential).²⁸

The combined exposure with respect to the S&P 500 Total Return Index is therefore roughly equivalent to a call option. However, the portfolio still keeps its long volatility exposure to the broad market thanks to the second component.

²⁸ The long straddle position from the trend-following index could also be replicated by some dynamic option strategy. The main advantage would be that the floor would be known and the strategy could be easily implemented. However, this would be very costly. Many investors are not willing to pay such high costs. Kulp et al. (2005) show that by investing in a managed futures index, an investor can replicate a long volatility exposure 9.5% cheaper than it can be bought in the option market.
Figure 10: Return Histograms and Robust Local Regression (LOESS) of Monthly Returns of Three Not Directly Investable Systematic Return Strategies versus the S&P 500 Total Return Index

Source: Bloomberg L.P. Monthly data as from 30.12.1999 to 29.08.2014. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.
From Figure 10 and Table 6, we see that the total return of the combined portfolio falls between that of the carry and the trend-following strategies. Interestingly, although both individual strategies have significant drawdowns (32.7% and 11.8%, respectively), the maximum drawdown for the combined portfolio is reduced to 13.8% as a result of the beneficial covariance properties of the two strategies.

In Table 6, we can see that excess kurtosis and negative skewness are reduced when compared with the values presented for the carry strategy. Hence, we should expect more stable returns in terms of lower drawdowns for the overall portfolio, which plays in favor of absolute-return-oriented investors.

Figure 11: Performance of CBOE S&P 500 PutWrite Index, Barclay Systematic Traders Index, S&P 500 Total Return Index and a 50 : 50 Combination of the PutWrite Index and Systematic Traders Index

Table 6: Return Statistics of CBOE S&P 500 PutWrite Index, the Barclay Systematic Traders Index and a 50 : 50 Combination

<table>
<thead>
<tr>
<th>Statistics</th>
<th>CBOE S&amp;P 500 PutWrite Index</th>
<th>Barclay Systematic Traders Index</th>
<th>50 : 50 Combination</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Return</td>
<td>144.5%</td>
<td>77.6%</td>
<td>117.7%</td>
</tr>
<tr>
<td>Return p.a.</td>
<td>6.3%</td>
<td>4.0%</td>
<td>5.4%</td>
</tr>
<tr>
<td>Volatility</td>
<td>11.4%</td>
<td>8.1%</td>
<td>6.3%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.59</td>
<td>0.53</td>
<td>0.87</td>
</tr>
<tr>
<td>Skewness</td>
<td>-1.80</td>
<td>0.33</td>
<td>-0.47</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>7.36</td>
<td>0.56</td>
<td>1.26</td>
</tr>
<tr>
<td>Maximum Drawdown</td>
<td>32.7%</td>
<td>11.8%</td>
<td>13.8%</td>
</tr>
</tbody>
</table>

Source: Bloomberg L.P., own calculations. Monthly data as from 31.12.1999 to 29.08.2014. Indices are not directly investable. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.
It is well known that in risk-off markets, the correlations between asset classes rise, and this usually implies that large drawdowns may be highly correlated across asset classes. This confirms the dilemma that diversification benefits typically diminish exactly when investors need them the most.

In Figure 12, we look at the correlation coefficients of six systematic return strategies – three carry strategies\(^{29}\) (blue diamonds) and three trend-following strategies\(^{30}\) (gray diamonds) over three time periods: the full period, the crisis period of the Lehman Brothers collapse and the subsequent recovery.

Over the full period, we see that our carry strategies show a high correlation to the equity market. The correlation moves closer to 100% during the crisis period, while in the subsequent recovery the carry strategies, as expected, are also highly correlated to the equity market. On the other hand, trend-following strategies show a somewhat low correlation to the equity market over the full period, but a high negative correlation during the crisis period. During the recovery period, trend-following strategies are again positively correlated to the equity market due to the adaptive nature of their market exposure.

These findings lead to two conclusions. First, we see the empirical behavior again as a confirmation of the effectiveness of our simple classification scheme. Second, it does not pay for absolute-return-oriented investors to place too much confidence in the diversification effect of a basket of carry strategies. As we have shown, during a crisis period, all strategies that are “short a put” exhibit an almost perfect downside correlation to the equity market. On the other hand, a basket of trend-following strategies could add diversification benefits to the portfolio during such crisis times.

Now let us take a look at how the strategies contributed to the bottom line. During the crisis period, the equity index lost half its value, whereas the three carry strategies lost 30%, 23% and 31%, respectively. Trend-followers, on the other hand, gained an impressive 28%, 48% and 64%, respectively, when measured by total returns. When looking at the recovery period, the S&P 500 shows a return of +102%, which means that all of the early losses were fully recovered. The carry strategy also posted strong returns (+74% for the CBOE S&P 500 PutWrite Index, +34% for the UBS American Volatility Arbitrage Index and +33% for the J.P. Morgan G10 FX Carry Index). The trend-following strategies appreciated as well.

Figure 12: Correlation Coefficients of Six Exemplary Systematic Return Strategies with the S&P 500 Total Return Index for Full Period, Crisis Period and Recovery Period (Compare with Table 7)


\(^{29}\) CBOE S&P 500 PutWrite Index, UBS American Volatility Arbitrage Index, J.P. Morgan G10 FX Carry Index.

\(^{30}\) Winton Futures Fund, Credit Suisse Tail Risk Strategy Index, J.P. Morgan Mean Reversion Index.
Hence, we see that the strategies with the highest drawdowns during crisis periods are typically the ones that deliver the highest drawups during recovery periods. The implications of our statistical analysis for absolute-return investors now become apparent. **Investors should strive for a balance between concave and convex strategies to lower the overall drawdown risk of their portfolios.**

<table>
<thead>
<tr>
<th>Table 7: Return Statistics of S&amp;P 500 Total Return Index and Three Concave and Three Convex Systematic Return Strategies</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Statistics</strong></td>
</tr>
<tr>
<td>S&amp;P 500 Total Return Index</td>
</tr>
<tr>
<td><strong>CRISES PERIOD</strong></td>
</tr>
<tr>
<td>Total Return</td>
</tr>
<tr>
<td>Return p.a.</td>
</tr>
<tr>
<td>Volatility</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
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<tr>
<td>Maximum Drawdown</td>
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<tr>
<td><strong>RECOVERY PERIOD</strong></td>
</tr>
<tr>
<td>Total Return</td>
</tr>
<tr>
<td>Return p.a.</td>
</tr>
<tr>
<td>Volatility</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
</tr>
<tr>
<td>Maximum Drawup</td>
</tr>
</tbody>
</table>

Source: Bloomberg L.P., own calculations. Monthly data as from 28.09.2007 to 27.02.2009 (top) and as from 27.02.2009 to 31.07.2012 (bottom). Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.

2.2 Guiding Principles for Selecting Systematic Trading Strategies

In practice, it is impossible to consider the entire universe of systematic return strategies for portfolio construction. Since systematic strategies are dynamic combinations of assets traded in the market, there is an unlimited number of strategies. They often differ only in minor details such as signal filters, volatility targets, etc. Therefore, preselection becomes an important step in building a systematic return portfolio. In this section of the primer, we summarize guiding principles.
A Sound Economic Rationale Can Help to Select More Sustainable Return Sources

The more that potential strategies are tested against historical data, the greater the likelihood of finding one that looks very attractive – most probably by chance alone. One effective way to protect oneself against these false positives is to require a sound economic rationale that can explain why a specific strategy should be sustainable. The probability of a systematic strategy having both an attractive backtest and a suitable economic rationale is significantly lower than for it having just an attractive backtest. Of course, this leaves the possibility of an attractive strategy getting discarded because one was not able to see the economic rationale at the time. However, not rejecting them in these instances would most likely result in more severe consequences for investors. It should also be noted that the negative impact of selecting an unattractive systematic strategy with both an attractive backtest and economic rationale is much smaller compared to selecting an unattractive strategy based on a positive backtest alone.32

Preference for Simple Strategies

When selecting strategies, Occam’s razor33 is another useful guiding principle. Strategy developers like investment banks, for example, usually develop complex systematic return strategies. It is easier to find attractive strategies since the search space of more complex strategies is bigger than that of simple strategies. Second, the complexity obscures transparency and causes higher implementation and trading costs. The more free parameters a strategy has, the higher the risk of overfitting to historical data. This means that a longer live track record is needed to decide whether a strategy really delivers what it is promising.

Costs Are Often Not Negligible

Paying attention to costs is also crucial when selecting systematic strategies. There are many direct and indirect costs associated with a systematic strategy, for example trading costs, structuring costs, market impact costs (slippage), etc.34 Trading costs increase with turnover and bid-ask spreads. Often, choosing strategies with lower turnover or more liquid underlyings can add value. For example, the same strategy with an equivalent fixed exposure is often more attractive when compared to its volatility-controlled version.

Transparency and competition between strategy providers can also help to keep costs down. So, choosing generic strategies over proprietary ones and using a best-in-class selection approach should be preferred. Transparency (required by regulators for example) can also have negative side effects. The US Natural Gas Fund, for example, used to publish the exact roll dates and specific future contracts of its systematic natural gas roll schedule. With more than USD 4 billion in assets under management at the beginning of 2010, it made for an easy target for front running.

Awareness of Capacity, Liquidity and Market Impact

Risk premia are the rewards for taking certain risks that other market participants are not willing to take or not capable of bearing. Risk premia returns are risky and cannot be seen as pure arbitrage opportunities.35 This also means that risk premia are not constant. The price of risks changes over time due to the arrival of new information. However, sometimes one can observe cycles where money is rushing into a certain risk premium chasing returns. It is important to recognize such phases and to adapt to the new risk/return regime. This is because during periods when a risk premium is stretched thin, even small external shocks can lead to sudden reversals and losses.

31 The danger is that backtested performance figures are the result of unintended data snooping, especially when there are many parameters. Any backtest model that is only in-sample (with perfect hindsight) and lacks out-of-sample test qualities should be rejected out of hand.

32 See Bailey et al. (2014) for a comprehensive discussion of backtesting problems.

33 Occam’s (sometimes Ockham’s) razor is a principle attributed to the English Franciscan friar William of Ockham (1287–1347). The original principle states that “Pluralitas non est ponenda sine necessitate,” which translates to “Entities should not be multiplied unnecessarily.” It is usually interpreted as preferring simpler over more complex theories/explanations if they make the same predictions.

34 As Frazzini et al. (2012) show, real trading costs make short-term reversal strategies unprofitable. However, size, value and momentum are profitable after adjusting for trading costs. They conclude that those return sources can be implemented and scaled up. Lesmond et al. (2004) argue that returns from momentum strategies (buying past winners and selling past losers) do not exceed trading costs. They claim that abnormal returns create an illusionary profit opportunity.

35 Many systematic trading strategies involve unfunded instruments. The decision of how much notional value to employ therefore becomes a bit arbitrary. One way to determine the leverage is to target a specific volatility and dynamically set the notional value accordingly.

36 See also Appendix 3.
Inflows into risk factors can have very different effects, depending on whether returns are driven mainly by mark-to-market effects or realized cash flows. This is mainly related to the time horizon of the instruments employed. We consider some examples below.

Thirty-year US Treasury bonds mainly have interest-rate risk. Their yield is the reward for bearing this risk. If the US Treasury market experiences large money inflows, one can expect yields to decrease. This means mark-to-market gains, which can be viewed as advance coupon payments. Since the time horizon of the instrument is rather long, the mark-to-market effects outweigh the effect that realized cash flows in the future will be lower. Large inflows in such a market will lead to above-average performance gains.

However, if we consider a portfolio of short-term high-yield bonds, the effect is less pronounced or even the opposite. With short-term high-yield bonds, credit risks dominate. Large money inflows will compress credit spreads. The mark-to-market effect will be small due to the short duration, but the coupon payments of new bonds will be much lower and over the period of a year or so will be below average. A similar effect for merger arbitrage strategies is explained by Mitchell and Pulvino (2001).\(^{27}\)

The same is true for more nontraditional risk premia such as volatility risk premia, for example, where the underlying systematic return strategy involves the selling of variance swaps. A short variance swap position accumulates the difference between implied and realized variance typically for major equity indices. The profit and loss (PnL) consists of a realized part since inception and an expected value of the nonrealized part of the remaining life of the swap. Large inflows, i.e., from sellers of variance/volatility, can depress the implied volatility. This is beneficial for the mark-to-market of the nonrealized part, which is more pronounced the longer the remaining life span of the swap is. Given that the realized volatility remains constant, a lower implied volatility lowers the future PnL. Depending on the maturity of the swaps, inflows into this strategy can lead to increasing or diminishing returns.

Understanding and monitoring such movements are crucial because real money flows are often not directly observable. Active management in this regard can prevent investors from riding an overextended horse.

### 2.3 Portfolio Construction Using Systematic Return Strategies

Earlier in this report, we argued that systematic return strategies are more suitable for portfolio construction due to their very attractive correlation properties (see Figure 2 and Figure 12). Therefore, the full potential of systematic return strategies can only emerge when they are combined within a portfolio in a suitable way.

The portfolio construction issue is usually embedded into a probabilistic framework by regarding the future returns as random variables with unknown probability distributions. If the investor is aware of his or her utility function \( U \), the portfolio weights \( w^* = (w_1^*, \ldots, w_n^*) \) are given by the solution of the following optimization problem:

\[
w^* = \arg\max_w E[U(w)].
\]

In words, the weights are chosen in such a way that the expected utility for the investor is maximized. The utility function corresponding to the prominent mean-variance portfolio is defined as \( U(w) = \mu'w - \frac{1}{2}w' \Sigma w \), with \( \mu \) denoting the random vector of returns and \( \Sigma \) the random covariance matrix.

This approach to portfolio construction is well-established and standard market practice. However, it is not without certain pitfalls—and these can be particularly severe for portfolios of systematic strategies. Here we would like to draw attention to the model risk and associated estimation risks.

In order to solve the portfolio optimization problem, the probability distribution of future returns is required. The usual approach is to choose a parameterized model for the returns in such a way that it captures relevant statistical properties of the returns. The parameters of the model are estimated so that the model provides a good fit to the observed return data. Once the model is calibrated, the probability distribution of the returns is fully specified.

Although the process seems to be straightforward, it introduces the risk of choosing an inappropriate model with potentially severe consequences (misallocations). A common pitfall is to choose a model that is too simple and thus ignores several statistical properties of the historical return time series. However, simple models are usually more tractable and the estimation risk tends to be smaller. Similarly, choosing a model that is very complex usually increases the estimation risk and introduces the risk of overfitting.

\(^{27}\) Mitchell and Pulvino (2001) show that merger arbitrage generates excess returns of +4% per year after transaction costs, Jelley and Ji (2010), however, find that the merger arbitrage spread has declined by more than 400 basis points since 2002. The authors attribute this to increased inflows into merger arbitrage hedge funds and reduced transaction costs.
The situation is particularly easy if the returns are assumed to be independent and identically normally distributed. In this case, the required parameters to calibrate the model are the expected values of the returns and the covariance matrix. Here, the average sample returns and sample covariance matrix correspond to the maximum likelihood estimates for the parameters, and, accordingly, it is enough to perform the optimization with these sample estimates from historical values. Inspired by this, some investment managers perform the portfolio optimization with sample estimates from historical values and implicitly assume that the resulting weights will be optimal for the out-of-sample period. However, if the model assumptions are not satisfied, this estimator will generally be biased (model error).

In the sample-based approach, the maximum likelihood estimators as given by the sample values agree with the “true” values only asymptotically, that is only if the sample size tends to infinity and, accordingly, the size of the estimation error is particularly high for small sample sizes. This can be a serious problem for systematic return strategies because the available historical time series, in general, are much shorter than those for traditional assets. Some instruments used to construct certain systematic return strategies have only been introduced over the past four decades. For example, exchange-traded options and VIX futures started trading on the Chicago Board Options Exchange (CBOE) in 1973 and 2004, respectively.

The realized estimation error is given by the difference $U(\mathbf{w}^*) - \hat{U}(\hat{\mathbf{w}}^*)$, where $\hat{U}(\hat{\mathbf{w}}^*)$ corresponds to the maximized utility based on the estimated parameters, that is, $\hat{U}(\hat{\mathbf{w}}^*) = \hat{\mu}^\top \hat{\mathbf{w}}^* - \hat{\mathbf{w}}^* \hat{\Sigma} \hat{\mathbf{w}}^*$ for the estimated expected returns and covariance matrix given by $\hat{\mu}$ and $\hat{\Sigma}$. This difference can be quite severe. DeMiguel et al. (2009) compared the out-of-sample performance of sample-based portfolio optimizers and found that none of them were consistently better in terms of popular risk-adjusted performance measures such as the Sharpe ratio when compared to the naive diversification strategy given by the equally weighted portfolio. He concluded that relative to the naive strategy, the benefit from the portfolio optimization was often more than offset by estimation errors.

We conducted a similar experiment in Appendix 4 and investigated the relationship between the size of the estimation error and the risk-adjusted portfolio performance. We found that portfolio optimization can underperform naive diversification if the estimation errors become too large. Most important is the asymmetry of the effect: estimation errors can only negatively affect the optimal portfolio since, trivially, every deviation from the optimum leads to inferior results.

Michaud (1989) described this effect as an "error-maximizing" property inherent in many optimization procedures, especially mean-variance, where even small estimation errors can jeopardize the entire optimization endeavor. In particular, short time series, many parameters to calibrate and a large number of assets tend to increase estimation errors. Investment professionals employing optimization techniques should be aware of this effect and should analyze potential negative consequences.

In the next section, we show how moving away from the in-sample optimal portfolio while maximizing portfolio entropy can help out-of-sample performance.
2.4 Case Study 1: Portfolio Diversification with Entropy Measures

So far, we have discussed potential pitfalls that arise in the construction of “optimal” portfolios of systematic return strategies by introducing the notions of model risk and estimation risk. The purpose of this case study is twofold. First, we quantify the effect of those risks on optimized portfolios in terms of various performance and risk measures, and second, we introduce a simple but highly effective method to mitigate some of those risks.

It is well known that portfolio optimizers are very sensitive to the input parameters \(^{39}\) and, accordingly, minor model misspecifications and estimation errors can lead to drastically altered “optimal” allocations. In layman’s terms, the portfolio optimizer has 100% confidence in the input data and, accordingly, has no issues with assigning extreme weights.

There are several methods that address this problem by including an additional input parameter, which reflects the uncertainty incorporated in the estimates. Popular examples include the Black-Litterman model, Meucci’s entropy-pooling approach and several shrinkage methods.\(^ {40}\) The common underlying idea of these methods is the introduction (explicitly or implicitly) of a neutral probability distribution of the returns (a neutral benchmark) that is blended with the input data.

The basic intention is to obtain weights that are in between the neutral benchmark and the weights that correspond to the estimated return distribution such that the deviation from the neutral benchmark should be in an inverse relationship to the uncertainty with respect to the estimated quantities.

In other words, the optimization result is being pulled toward the neutral benchmark. In the event that the estimates are very uncertain, it essentially results in weights of the neutral benchmark. At the other extreme, if the estimates are certain, the neutral benchmark has no effect and the optimization is entirely based on the estimated parameters. In general, the estimated parameters will be blended with the neutral benchmark.

It should be noted that the highlighted words require the notion of a distance between potential sets of weights. If we rule out the possibility of short positions and leverage, the weights will lie between 0% and 100% and will add up to 100%, just like a probability distribution. And for these, a well-understood notion of distance is given by the entropy (or cross-entropy).\(^ {41}\) Below, we demonstrate how entropy can be used to efficiently deal with estimation errors.

For traditional assets, the market portfolio is a natural choice as a neutral benchmark. Since no such market portfolio exists for systematic return strategies, the maximum entropy, i.e. the equally weighted portfolio, is a common choice. Here, the entropy can be interpreted as a measure of diversification since – in the absence of any reliable estimates – the equally weighted portfolio promises the maximum out-of-sample diversification.\(^ {42}\) Any deviation from this portfolio leads to a potentially smaller diversification and should be justified by the existence of reliable estimates.

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\(^ {39}\) See Best and Grauer (1991).
\(^ {40}\) See also Stefanovits et al. (2014) for a very recent account of this and the references therein.
\(^ {41}\) Note that short and leveraged positions can both be incorporated by using the generalized entropy measure.
\(^ {42}\) Trivially, if reliable information on the distribution exists, the maximum diversified portfolio will, in general, differ from the maximum entropy portfolio. For example, if two of the assets in a portfolio are linearly dependent (with high confidence), the equally weighted portfolio would assign a combined weight to those assets that is too high when compared to the weights of the maximal diversified portfolio.
Next, we will discuss a particularly simple and straightforward method to employ this notion, which is inspired by the Optimal Portfolio Diversification Using Maximum Entropy Principle authored by Bera and Park (2008). The key finding is that sacrificing in-sample optimality in favor of increased entropy (in the weight’s space) potentially increases the out-of-sample performance.

We consider the following portfolio optimization problem: given the in-sample optimal weights $w^* = \arg\max_w U(w)$ and the corresponding in-sample maximal utility $U(w^*)$, the constraint maximum entropy weights $w^{\text{ent}}$ are given by:

$$w^{\text{ent}} = \arg\max_w H(w)$$ subject to $U(w^{\text{ent}}) \geq a \cdot U(w^*)$,

where the confidence parameter $a$ is a number between 0 and 1$^{43}$ and $H(w)$ is the entropy$^{44}$ corresponding to the weights $w = (w_1, ..., w_n)$. The parameter $a$ indicates the confidence in the estimates of the risk model: the closer to one, the less the portfolio optimizer is allowed to deviate from the in-sample optimum. An $a$ of zero would be appropriate if there were a complete disbelief in the in-sample estimates, while a value of one would be appropriate if there were full confidence in the in-sample estimates. However, in the presence of model and estimation risk, this relationship does not necessarily remain valid, and sacrificing in-sample optimality (by choosing the confidence parameter $a < 1$) and thereby increasing the entropy might actually increase the out-of-sample utility.

The impact of model misspecifications and estimation errors can be demonstrated by comparing the utility of in-sample and out-of-sample optimized portfolios using the same sample estimators.$^{45}$ In fact, if there were no model or estimation errors, the optimal in-sample weights should also be optimal for the out-of-sample period. This implies that the out-of-sample utility should increase with increasing values of the parameter $a$. However, in the presence of model and estimation risk, this relationship does not necessarily remain valid, and sacrificing in-sample optimality (by choosing the confidence parameter $a < 1$) and thereby increasing the entropy might actually increase the out-of-sample utility.

Now, let us investigate a concrete example using the systematic return strategies introduced in section 4. Here the utility function is chosen to be the Sharpe ratio$^{46}$

$$w^{\text{ent}} = \arg\max_w H(w)$$ subject to $\text{Sharpe Ratio}(w^{\text{ent}}) \geq a \cdot \text{Sharpe Ratio}(w^*)$.

In words, we determined the maximum entropy weights in such a way that the corresponding Sharpe ratio does not deviate too much (as controlled by the confidence parameter $a$ from the optimal in-sample Sharpe ratio. This is schematically visualized in Figure 13.

43 Note that in the language of Appendix 5, this is the maximum-entropy estimate such that the corresponding utility $U(w^{\text{ent}})$ does not deviate too much (as controlled by $a$) from the in-sample optimum utility given by $U(w^*)$.

44 By using entropy, the neutral benchmark is the equally weighted portfolio. Any other neutral benchmark can be chosen by using the cross-entropy instead of entropy. See Appendix 5 for a detailed discussion of the entropy concept.

45 In the mean-variance case, the sample-estimators are given by the average returns and the sample covariance matrix of the in-sample period.

46 Any other utility function or risk measure (after a slight modification) is possible as well. For example, the popular VaR or CVaR risk measures would have been equally suitable.
Table 8: Summary of In-Sample Statistics

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Mean-Variance</th>
<th>Constrained Maximum Entropy</th>
<th>Maximum Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Return</td>
<td>365.2%</td>
<td>278.7%</td>
<td>142.0%</td>
</tr>
<tr>
<td>Return p.a.</td>
<td>11.8%</td>
<td>10.2%</td>
<td>6.6%</td>
</tr>
<tr>
<td>Volatility</td>
<td>4.4%</td>
<td>4.3%</td>
<td>6.4%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>2.59</td>
<td>2.26</td>
<td>1.03</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.69</td>
<td>0.34</td>
<td>-1.22</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>8.25</td>
<td>4.64</td>
<td>5.98</td>
</tr>
<tr>
<td>Maximum Drawdown</td>
<td>7.9%</td>
<td>7.1%</td>
<td>21.7%</td>
</tr>
</tbody>
</table>

Source: Bloomberg L.P., own calculations. Monthly data as from 30.11.2000 to 29.08.2014. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.
As expected, in-sample the mean-variance portfolio showed the best results when measured by the Sharpe ratio. The maximum entropy portfolio was the weakest, and the constrained maximum entropy portfolio lies in the middle, both in terms of total return and Sharpe ratio. This changes significantly when considering the out-of-sample performances shown in Figure 15 and Table 9.

We see that if the optimal in-sample weights are applied to out-of-sample data,\(^47\) the mean-variance portfolio hardly beats the maximum entropy portfolio and is significantly inferior to the constrained maximum entropy portfolio in terms of total return, volatility and, accordingly, also in terms of the Sharpe ratio.

There are several important lessons to learn here. First, the in-sample mean-variance optimized portfolio performance points to a high overall cumulative return, whereas out-of-sample this methodology gives a drastically lower number. Second, the in-sample mean-variance optimization overestimates the diversification effect and underestimates the drawdown risk because estimation errors are ignored.

Third, the constrained maximum entropy represents a balance between in-sample optimality and portfolio entropy, depending on one’s confidence in the in-sample estimates. The constrained maximum entropy strategy dominates both the mean-variance portfolio and the naively maximum entropy diversified portfolio in key performance indicators in Table 8.

Summing up, the constrained maximum entropy method is straightforward to implement and can potentially significantly improve the risk-adjusted out-of-sample performance of a systematic return portfolio.\(^48\) It is evident that the benefits of this method will be particularly prominent if model and estimation risk is high, which is often the case, not only for systematic return strategies.

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**Table 9: Summary of Out-of-Sample Statistics**

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Mean-Variance</th>
<th>Constrained Maximum Entropy</th>
<th>Maximum Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Return</td>
<td>94.5%</td>
<td>122.4%</td>
<td>142.0%</td>
</tr>
<tr>
<td>Return p.a.</td>
<td>5.0%</td>
<td>6.0%</td>
<td>6.6%</td>
</tr>
<tr>
<td>Volatility</td>
<td>4.8%</td>
<td>4.5%</td>
<td>6.4%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>1.04</td>
<td>1.31</td>
<td>1.03</td>
</tr>
<tr>
<td>Skewness</td>
<td>-1.13</td>
<td>-0.64</td>
<td>-1.22</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>5.08</td>
<td>1.79</td>
<td>5.98</td>
</tr>
<tr>
<td>Maximum Drawdown</td>
<td>11.5%</td>
<td>7.8%</td>
<td>21.7%</td>
</tr>
</tbody>
</table>

Source: Bloomberg L.P., own calculations. Monthly data as from 30.11.2000 to 29.08.2014. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.

\(^47\) We applied the in-sample weights, which were based on an estimation period of 12 months subsequent to the next month.

\(^48\) An attractive side effect is the lower portfolio turnover, which helps to lower transaction costs and might require less market liquidity for rebalancing.
2.5 Case Study 2: The Effect of Adding Systematic Return Strategies to a Balanced Portfolio

In this second case study, we illustrate the effect of adding systematic return strategies to a classic balanced portfolio consisting of 60% equities and 40% bonds.\footnote{We took 60% of the MSCI Daily TR Net World USD (NDDUWI) and 40% of the Barclays Global Aggregate Total Return Index (LEGATRUU) with monthly rebalancing.} As for systematic return strategies, we are using the out-of-sample constrained entropy portfolio of the last section. We analyze the total return, the Sharpe ratio and the maximum drawdown of the combined portfolio consisting of the constrained entropy and balanced portfolios. The weights of the former range from 0% to 100% – in other words, from purely balanced to purely systematic. In the upper half of Figure 16, we see the cumulated performances of balanced, constrained entropy and the combination of both in equal weights. While the total return is about the same, the superior diversification properties of the systematic return manifest themselves in the evidently smoother returns.

In the lower half of Figure 16, we show the combination of total return and maximum drawdown for each combination of balanced and constrained entropy portfolios, with highlighted cases given by the 100%, 50% and 0% weights of the systematic return portfolio. It is evident that the inclusion of systematic return strategies primarily reduces the risk while keeping the total return virtually unchanged. In particular, an inclusion of 50% reduces the maximum drawdown by almost 50% while the total return essentially stays the same.

![Figure 16: Performance Comparison](image-url)

Performance comparison between classical balanced portfolio, constrained entropy portfolio of systematic return strategies and 50:50 mix of both. Source: own calculations. As from 30.11.2000 to 29.08.2014. Strategies are not directly investable. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance. Performance indications do not consider commissions, fees and other charges, including commissions levied at subscription and/or redemption.

\footnote{We took 60% of the MSCI Daily TR Net World USD (NDDUWI) and 40% of the Barclays Global Aggregate Total Return Index (LEGATRUU) with monthly rebalancing.}
Figure 17 summarizes the isolated effect on the portfolio’s Sharpe ratio and maximum drawdown for each added weight of the systematic return portfolio. We have highlighted the effect at a weight of 20%. We see that the Sharpe ratio can be doubled and the maximum drawdown can be reduced by three-quarters. In particular, by adding 20% of systematic strategies, we see that the Sharpe ratio could be increased from 0.57 to 0.67 and the maximum drawdown could be reduced from 36% to 30% as the total return remains virtually unchanged (moving from 101.35% to 101.21%).

We therefore conclude that adding systematic return strategies to classic balanced portfolios can substantially increase their diversification potential, with a significantly reduced maximum drawdown and an increased Sharpe ratio.

Figure 17: Sharpe Ratio (left) and Maximum Drawdown (right) of a Combined Position Consisting of a Traditional Balanced Portfolio and a Portfolio of Systematic Return Strategies

The percentage weight of the systematic return strategies is denoted on the x-axis. The highlighted points correspond to the combination of 20% systematic return strategies and 80% balanced portfolio. The effect is an increase in the Sharpe ratio from 0.57 to 0.67 and a reduction in the maximum drawdown from 36% to 30%.

Source: own calculations. As from 30.11.2000 to 29.08.2014. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance.
3. Implications for Investors

Systematic return strategies are nondiscretionary investment rules that aim to monetize the performance potential from established and well-documented risk premia in asset classes. Adding them to a balanced portfolio can lead to higher return persistency and thus portfolio robustness.

In this section, we show how investors can overcome the common pitfalls when dealing with systematic return strategies. We highlight again how important it is to have not only an effective classification scheme, but also a deep understanding of how risk premia harmonize with each other to unlock the full potential from these interesting investment solutions. In the conclusion, we underline our firm belief that the future for systematic return strategies looks bright, as more and more investors start to realize how these strategies can help to diversify their portfolios and particularly their core fixed-income holdings to achieve their investment targets in both falling and rising interest-rate environments.
3.1 Overview
We would like to summarize the key findings before moving to the conclusion:

- By using systematic return strategies, investors can access additional diversification benefits. At the same time, they can enjoy sufficient liquidity since most of the strategies are based on liquid traditional asset classes. We have seen that due to the convex or concave nature of systematic return strategies, linear concepts such as Sharpe ratios are not sufficient to explain the risk/return profile. A more appropriate risk-adjusted return comparison would at least need to include the convexity.

- Our simple classification scheme shows that if only carry strategies are chosen, this might have limited diversification potential during crisis periods. However, the comovement of carry strategies across different asset classes is one of our central critical points and suggests that they are mainly influenced by general risk aversion in crisis periods.

Therefore, it is important that absolute-return investors combine concave (carry) strategies with convex (trend-following) strategies. Investors can use these strategies as building blocks to remodel the return distribution of their fixed-income or balanced portfolios, introducing positive skewness to mitigate downside risks.

- Positive convexity in itself is not a “free lunch.” The investor should carefully analyze the upside and downside properties of the relevant strategies. Trend-following strategies need trending markets. However, this means that they are not consistently profitable. As with positive gamma or positive convexity trades in general, many trend-following strategies are not profitable. They usually lose a little, but can earn a lot in strong-trending markets. The performance of individual trend-following strategies may vary substantially. Hence, performance dispersion among strategies may be very wide because they depend on choosing the right markets. In addition, the investor is still exposed to gap risk – the risk that the strategy is not fast and nimble enough to adapt to sudden changes in markets.

- In a world of growing complexities, we firmly believe that “simplicity is key.” Our guiding principles can help investors to navigate the universe of systematic return strategies. We stressed that costs, liquidity and capacity constraints play an important role. However, most importantly, we have shown that strategies need to be based on sound economic rationales. Active management can provide an edge in this respect.

- We demonstrated that systematic strategies exhibit lower pair-wise correlations compared to traditional asset classes (please also see Figure 2). This means that increasing the number of different systematic return strategies in a portfolio can substantially reduce portfolio risk. Portfolio theory describes how to determine their respective weights. However, model and estimation errors are serious challenges in practical portfolio optimization. For this reason, optimized portfolios are not necessarily optimal portfolios. In Appendix 4, we show that portfolio optimization with large enough estimation errors can even be expected to underperform naively diversified portfolios. Additionally, positive properties like low correlations, short time series, skewed return distributions and nonlinear relationships to traditional asset classes compound model and estimation errors. Therefore, particular steps have to be taken to mitigate some of the adverse effects of model and estimation errors. This is especially true for systematic return strategies. So we presented the constrained maximum entropy method and showed how it can help to build more stable and robust systematic return portfolios.

- Path dependency requires special attention. Many investors have experienced that even simple stop-loss rules from risk management can introduce the risk of path dependency in the return-generating process of the portfolio. This means that initial decisions in the risk management framework may limit future portfolio choices even though the circumstances under which those decisions were based may no longer be relevant. In general, the more successful a particular risk management strategy has been in the past, the more likely it will lead to inflexibility. When decisions are made based on past experience, other options are ruled out and a path emerges that often becomes irreversible as the investor gets locked into the path.

\[50\] Taleb (1997) provides a good overview on this.
3.2 Conclusion

In this report, we first examined the reasons why a typical balanced portfolio has done so well over the past three decades. Two drivers were identified. First, bonds and equities exhibited very reliable diversification, particularly in times of economic shocks. Second, interest rates have been declining globally over the last 30 years. These are also the reasons why many market professionals question the future return potential of such investments and fear higher drawdowns going forward.

Systematic return strategies may be a valuable alternative in this situation. After providing a definition of systematic return strategies and outlining some well-documented examples, we argued that risk premia investing is not new. Many investors already have direct or indirect exposure to this form of investing. However, indirect exposure – a portfolio of value stocks or small-cap stocks, for example – is still dominated by market beta and cannot take full advantage of the low correlation between value and small-cap risk premia. We pointed out that only direct exposure allows investors to take full advantage of the diversification benefits.

We introduced the concept of nonlinear payouts from the option theory and investigated the empirical nonlinear relationships to the market of several systematic return strategies. We argued that a simple classification scheme (carry and trend-following) based on the positive or negative convexity of the strategy can help investors to avoid overlaps in terms of tail-risk exposure and to construct more robust portfolios. We specifically argued that trend-following strategies can help to preserve capital in bear markets due to their notable risk-mitigating properties.

Furthermore, we presented principles that can be used as a guide for selecting systematic return strategies. We emphasized that strategies should be based on sound economic rationales and that they should be simple in order to avoid falling into the most common pitfalls.

In our first case study, we showed one way how investors can mitigate some of the effects of estimation errors using the constrained maximum entropy method. It became evident how sacrificing in-sample optimality in favor of portfolio entropy can help to construct more stable and robust portfolios.

In the second case study, we investigated how adding systematic return strategies to a balanced portfolio can help investors to earn higher risk-adjusted returns and reduce drawdown risks. Our approach offers an innovative framework for generating persistent returns from a portfolio of systematic return strategies that is effectively diversified.

A diversified basket of systematic return strategies across asset classes can deliver more stable portfolio returns due to its inherent correlation characteristics. Since the returns are not directly exposed to interest rates, a systematic return solution can be a viable way for both relative-return and absolute-return investors to diversify their portfolios. This is particularly true for their core fixed-income holdings.
Appendix

Appendix 1: Drawdowns and Drawups
Drawdown (DD) measures the current cumulative loss from the previous maximum price level within a given time span, i.e. given a price process $S$ and the considered time span $[t_1, t]$, the drawdown at time $t$ can formally be defined as:

$$DD(t_1, t) = \left| \frac{s_t}{\max_{t_1 \leq r \leq t} s_r} - 1 \right|$$

Drawup (DU) is just the opposite since it reflects the cumulative gain from the previous minimum. With the notation from above, it can be defined as:

$$DU(t_1, t) = \frac{s_t}{\min_{t_1 \leq r \leq t} s_r} - 1$$

The maximum drawdown and maximum drawup within a time span $[t_1, T]$ are accordingly given by:

$$\text{Max}DD(t_1, T) = \max_{t_1 \leq t \leq T} |DD(t_1, t)|$$

and:

$$\text{Max}DU(t_1, T) = \max_{t_1 \leq t \leq T} DU(t_1, t)$$

Appendix 2: Convexity of Systematic Return Strategies
The convexity of a strategy with respect to its (main) underlying describes a certain functional relationship. Typical examples are shown in Figure 18.

More formally, a function $f(x)$ of one variable $x$ is called convex if the line connecting any two points of its graph lies above the graph (left figure). It is called concave (negative convexity) if the line lies below the graph (right figure).

In the first case, an increase in the underlying’s return yields an increase in the strategy’s return at an increasing rate. In the second case, an increase in the underlying’s return yields a decrease in the derivative’s return at a decreasing rate. The corresponding examples for negative convexity are shown below.

The seminal study by Perold and Sharpe (1988) investigates the convexity of strategy values with respect to the value of risky assets (stocks). Strictly speaking, the authors consider the reaction of the strategy’s value to certain price scenarios of the underlying stock price over time. For instance, a monotone rise/fall in the stock’s price within a certain time period and simulated fluctuations are considered. In this setting, they arrive at the following findings:

- Strategies that purchase stocks as they fall in value and sell stocks as they rise in value lead to concave strategies. In periods of monotonically rising or falling stock prices, this type of strategy is inferior to linear (“buy-and-hold”) strategies. However, these strategies are superior in flat but oscillating markets. So, they are favorable in markets with small absolute movements but with high volatility in the underlying’s price.
- Strategies that sell stocks as they fall and buy stocks as they rise lead to convex strategies. Their qualitative behavior is just the opposite of concave strategies. In particular, this type of strategy loses against linear strategies in the absence of big price trends.
The convexity of a trading strategy is also strongly related to the gamma of a European option, i.e., the second derivative of the option’s price with respect to the underlying’s price. To highlight this relationship, we regard a systematic return strategy as a dynamic portfolio strategy known from the mathematical finance literature. We assume that the price process of the risky asset \( S \) (defined on some filtered probability space) is given by the (strong) solution of

\[
dS_t = S_t \mu_t \, dt + S_t \sigma_t \, dW_t, \quad S_0 = s,
\]

where \( \mu_t \) and \( \sigma_t \) are positive deterministic processes and \( W_t \) is a standard Brownian motion. For the sake of simplicity, we assume that interest rates are zero. A dynamic portfolio \( \phi = (\phi^0, \phi^1) \) is a stochastic process (adapted to the filtration generated by \( S_t \), i.e., \( \phi_t \) can depend on current time \( t \) and the price path of \( S \) up to time \( t \) that assigns at each time the number of shares in the risky asset \( S \) and the money market account. Accordingly, given some initial wealth \( x \), the strategy value \( V_t \) at each time \( t \) is given by

\[
V_t = x + \phi_t^0 + \phi_t^1 S_t.
\]

We further assume that the strategy is self-financing, meaning

\[
V_t = x + \int_0^t \phi_s^1 \, dS_s
\]

for all \( t \geq 0 \). This assumption is standard and means that besides the initial investment \( x \), changes in the strategy’s value are solely due to price changes in the risky asset given the allocation \( \phi_t^1 \).

Now, given a European option claim \( H \) (meeting standard regularity assumptions) on the risky asset \( S \) with maturity \( T \), we have the following well-known decomposition

\[
H = \Pi(0, H) + \int_0^T \Delta_t \, dS_t,
\]

where \( \Pi(0, H) \) denotes the initial price of the option and \( \Delta_t \) the option’s delta at time \( t \), that is, \( \Delta_t = \frac{\partial}{\partial S_t} \Pi(t, H) \). This relationship reflects the well-known paradigm (given, for example, in the Black-Scholes setting) that under suitable assumptions (e.g., no volatility risk), any European option payoff can be replicated by an initial investment and a delta-hedging portfolio. European options therefore can be decomposed into an initial investment and a systematic return strategy.

In certain cases this point of view can be reversed. Formally, given a fixed maturity time \( T \) and a systematic return strategy \( \phi \) on a price process \( S \), we can define the “option” \( H \) (note that \( H \) is not necessarily nonnegative) by

\[
H_t := x + \int_0^T \phi_t \, dS_t,
\]

where the initial investment \( x \) is understood as the “price” of the option \( H \) and \( \phi \) naturally corresponds to the option’s delta. In this case, the option’s gamma is given by \( \Gamma_t = \frac{\partial^2}{\partial S_t^2} \Pi(t, H) \), and accordingly we could say that the systematic return strategy is convex if \( \Gamma_t \geq 0 \) for all \( t \geq 0 \) and concave if \( \Gamma_t \leq 0 \) for all \( t \geq 0 \). Thus, for this class of systematic return strategies, the convexity of the strategy is equivalent to the nonnegative gamma of the corresponding option.

A slightly different decomposition is suggested by Bruder and Gausel (2011), which we will introduce next. This decomposition is less straightforward, but leads to very similar qualitative findings as those by Perold and Sharpe (1988) summarized above. They define the option profile by \( H(S_t) := \int_0^T \phi(x) \, dx \) (note that \( H \) is not necessarily nonnegative). Then, a simple application of Itô’s formula yields

\[
V_T - V_0 = H(S_T) - H(S_0) - \frac{1}{2} \int_0^T \phi'(S_t) \sigma_t^2 S_t^2 \, dt.
\]

As above, we see that the corresponding option profile is convex if and only if \( \phi''(S_t) \geq 0 \) since \( \frac{\partial^2}{\partial S_t^2} H(S_t) = \phi''(S_t) \). Another consequence of this decomposition is that systematic return strategies corresponding to convex option profiles have a negative trading impact, and the reverse is true for systematic return strategies leading to concave option profiles. In particular, in flat markets we have \( H(S_T) - H(S_0) = 0 \), and accordingly the trading impact dominates the strategy’s value, which increases with volatility.
Appendix 3: Systematic Return Strategies and the Efficient Market Hypothesis

Some market participants have expressed criticism about risk premia investing. This criticism mostly falls into two categories. First, they argue that investing in traditional assets already gives some exposure to these risk premia. We addressed this concern in section 2. We argued that by directly investing in these risk premia – as opposed to an indirect investment via traditional long-only portfolios – the investment manager’s degree of freedom can be increased and he or she accordingly is more likely to achieve an “optimal” allocation. Also, many risk premia cannot be harvested with such simple portfolios. The second pillar of concern rests on the hypothesis that risk premia should not be regarded as “new” asset classes or risk factors. In conjunction with traditional equilibrium asset pricing models like the CAPM, this would imply – in an efficient market – that exposure to these risk premia is not expected to be rewarded beyond the indirect exposure to the traditional market factors. Here, we address this second concern by showing that it is indeed common sense that some of these risk premia should be regarded as additional risk factors that promise a premium, which is why they are called “risk premia.”

The Efficient Market Hypothesis (EMH) (Fama 1970) in its strong form asserts that all relevant information is publicly available and immediately reflected in the prices of financial investments. If investors are assumed to be risk-averse and agree on a single risk measure, this implies the existence of some “optimal” market portfolio that no single investment strategy should be able to persistently outperform on a risk-adjusted basis.

However, every now and then researchers and practitioners choose a particular market, for example an equity index, and claim to have spotted such an investment strategy and conclude by contradiction that markets cannot be efficient.51 Advocates of the EMH point to the joint hypothesis problem (Fama 1991), which states that the EMH cannot be rejected on the basis of a single market model. That is, an investment strategy might be superior to the market with respect to one risk measure, but inferior with respect to another. This problem is particularly evident in the earlier criticisms of the EMH, which were based on the (single-factor) CAPM.52 They found that certain investment strategies consistently outperformed others without having a higher beta (some investment managers called these the “manager’s alpha”) and concluded the invalidity of the EMH.53

The standard approach to support the EMH against such contradictions is to enlarge the corresponding market model. One of the earliest of these attempts came from Fama (1991), who showed that by extending the standard CAPM by two additional factors, many of the strategies that seem to be inconsistent with the EMH disappeared. Parts of the returns that could not be explained by the beta and were falsely attributed to alpha could now be assigned to the additional risk factors. Some investment managers call these additional factor exposures “alternative beta” or “exotic beta.”

According to the joint hypothesis problem, the EMH can be rejected only by an investment strategy that produces superior risk-adjusted returns in every possible market model, meaning for every possible (reasonable) risk measure. This is what Jarrow and his colleagues claimed to have done in a series of papers (see Hogan et al. 2004 and Jarrow et al. 2005). They introduced the concept of “statistical arbitrage” strategies, which are strategies that asymptotically generate riskless profits. Here, “riskless” means that the variance of the gains process vanishes as time passes, i.e. the randomness of the gains disappears when considering (very) long time horizons. This is obviously independent of any market model and cannot be explained by the introduction of further risk factors and, accordingly, is incompatible with the EMH. Using a rigorous methodology, they find that many of the investigated carry and trend-following strategies can be classified as statistical arbitrage with high confidence.

In summary, even if it is assumed that the EMH holds, unless the market portfolio includes all sources of risk with appropriate weights, it will be possible to find strategies that are exposed to a wider opportunity set that persistently outperform this particular market.

51 The existence of such seemingly inefficient markets is backed by the scholars of behavioral finance theory; see for example Shleifer (2000). Here, some concerns are formulated regarding the assumption of the “rational investor.”

52 Here, the risk premia of each single asset should correspond to its exposure to the market risk, the beta. Expected returns that are not backed by an appropriate beta are attributed to alpha. In equilibrium, according to the theory, this should equal the risk-free rate of return.

53 Note that when restricting to the narrow CAPM, the PutWrite strategy as well as the trend-following strategy we discussed in the previous section seem to violate the EMH as well.

54 In particular, they include most market frictions in their tests.
Appendix 4: Portfolio Optimization in the Presence of Estimation Errors

Optimization results can be far from optimal in the presence of estimation errors. Under certain circumstances, even naive portfolio construction schemes, i.e., equal weights, can be expected to lead to better results.

Let us start with 30 German large-cap stocks and estimate the returns and the covariance matrix based on the weekly returns between 30.12.2005 and 29.08.2014. Next, we perform a standard mean-variance portfolio optimization to optimize the in-sample Sharpe ratio, which we find to be 1.57. In practice, it is unrealistic to achieve such an attractive Sharpe ratio because here the optimizer was allowed to determine the portfolio weights based on known risks and returns of the investment period. Weights are fixed over the entire period. This reflects the hypothetical situation where risks and returns could be estimated without any errors. In real life, investors will have to estimate risks and returns employing whichever techniques he or she prefers.

Whichever estimation technique is employed, chances are that its estimation involves estimation errors. Let us take a conservative approach and ignore estimation errors in estimating the covariance matrix and model estimation errors of the returns in the following form: \( \hat{\mu} = \mu_i + \sigma_i \delta \varepsilon \) where \( \varepsilon \sim N(0,1) \) is standard normally distributed, \( \mu_i \) is the realized expected return, \( \sigma_i \) is the realized volatility of the asset and \( \delta \) is a parameter that determines the intensity of the estimation error. The model of estimation errors assumes that the estimation error of the return linearly increases with the volatility of an asset without any directional bias. The exact form of the model for the estimation error does not matter, for example \( \hat{\mu} = \mu_i + \delta \varepsilon \) leads to qualitatively similar results.

Next, we perform a Monte Carlo simulation of 250 realizations for each level of estimation error. Figure 19 shows the Sharpe ratio as a function of the estimation error intensity, \( \delta \). As expected, the average of the Sharpe ratio declines with growing estimation error. The maximum and minimum observed Sharpe ratios are shown as an envelope around the average. At around \( \delta \approx 0.5 \), the mean Sharpe ratio of the portfolio optimization drops below the one of a naively diversified (equally weighted) portfolio. This can be interpreted as meaning that in this setting, one cannot expect to outperform the naively diversified portfolio unless the standard deviation of one’s estimation error for expected returns is less than half that of the volatility of the respective asset.

Figure 19: Sharpe Ratio as a Function of Estimation Error Intensity, \( \delta \), Compared to a Naively Diversified Portfolio

![Figure 19](image)

Source: Bloomberg L.P., own calculations. Historical performance indications and financial market scenarios are not reliable indicators of current or future performance.

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55 We use the constituents of the Deutscher Aktienindex (DAX) as of March 2014.
56 Optimization constraints are 1) the sum of all weights equal to 100% \((1 = \sum_{i=1}^{n} w_i)\).
57 In-sample Sharpe ratios are naturally quite high, since the risk and return parameters are known in advance.
58 For example, some people rely on analysts looking at company balance sheets and talking to the company management. Others rely on quantitative methods (e.g., Merton 1980, Stein 1995) or on technical analysis.
Appendix 5: Maximum Entropy Estimates in Information Theory

From information theory we get a constructive answer to the statistical inference problem: “Given a discrete random variable for which we have only partial information about its probability distribution, what is the least biased estimate possible?” This is the maximum entropy estimate. The key for the maximum entropy estimate is the entropy measure that acts on probability distributions. For a discrete probability distribution \( p = (p_1, \ldots, p_n) \), the corresponding entropy is given by:

\[
H(p) = -\sum_{i=1}^{n} p_i \log(p_i)
\]

Now let \( X \) be a discrete random variable that can take a finite collection of states \( x_1, \ldots, x_m \), and denote its probability distribution by \( p = (p_1, \ldots, p_m) \). If we assume that we have only partial information about the probability distribution \( p \) and denote by \( \Omega \) the subset of all discrete probability distributions that meet the partial information we have about \( p \), then the **maximum entropy estimate** is given by \( q \), where:

\[
q = \max H(k) \text{ among all } k \text{ in } \Omega.
\]

This estimate is the least biased among all possible estimates that meet the partial information in the sense that it is the distribution that has the minimum distance to the most uncertain, i.e., the maximum entropy, distribution. Any other estimate that meets the partial information we have and that deviates from \( q \) has incorporated more information than given and has thus introduced a bias.

Although this expression seems somewhat arbitrary, it can be proven\(^{59}\) to basically be the **unique measure** based on three axioms matching our intuition regarding the amount of uncertainty of a given probability distribution. The three axioms are:

1) The measure should be higher for broader distributions (attaining its maximum if all states are equally likely).
2) The measure should be lower for sharply peaked distributions (attaining its minimum if only one state can be attained with positive probability).
3) The measure shall be additive for independent sources of uncertainty.

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\(^{59}\) See Jaynes (1957) for shortcut proof and the references therein.
Literature


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