UBS

Academic Research Monitor
Where is your next idea coming from?

Equities

Global
Quantitative

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An academic digest with a difference

We introduce our new Academic Research Monitor, which aims to provide a regular update on recent academic papers. It aims not just to review the academic work, but also to reproduce the results from a selection of papers in both different regions and more liquid universes.

This month's topics

This month, the focus of the Academic Research Monitor is on two topics that follow on from our recent Quantitative Conference in London: risk parity in its various forms and improving price momentum strategies.

Does a dynamic momentum strategy add value?

We implement risk-managed momentum strategies, as proposed by the two momentum papers that we review, and evaluate their performance across Europe, North America, Pacific Basin ex Japan and Japan. The approach of forecasting momentum returns conditional on the market direction adds value over the simpler constant volatility strategy in three out of the four regions we test.

Introduction

In this first edition of our Academic Research Monitor we review a number of papers in two areas: risk parity and price momentum, both of which we covered at our London Quantitative Conference in April 2013.

We aim to differentiate our reviews of research by, where it makes sense, reproducing the results in the research papers on other markets or more liquid sets of names. In this report, we show that the approach to improving the timing of exposure to price momentum described in "*Momentum Crashes*" appears to show an improvement over a simple volatility targeting approach in Europe, North America and the Pacific Basin ex Japan.

The two papers (see Figure 1) which aim to improve the returns to a momentum strategy do so by firstly trying to understand what causes momentum to crash (as it did during the period March-May 2009). The first approach involves a constant volatility adjustment; the second adds a conditional forecast of return to improve the performance beyond that of just targeting the volatility. The first approach seems similar to that suggested in our publication *Price momentum in Europe* (October 1, 2009).

Momentum timing works over the recent past in most of the regions we tested

Improving momentum's performance

Figure 1: Momentum papers

"Momentum has its Moments" *Pedro Barroso and Pedro Santa-Clara*	SSRN working paper, April 2013
"Momentum Crashes" *Kent Daniel and Tobias Moskowitz*	SSRN working paper, April 2013

Source: UBS

On 7 February this year, we published *Understanding risk parity – Getting performance out of risk parity*. The analysis in this paper was about extending the risk parity approach in two ways: creating long / short (or under- and overweight) portfolios and adding return estimates into the risk parity framework. Since the publication of this note, a number of other academic papers on the topic, listed in Figure 2, have come to our attention.

An update on risk parity research

Figure 2: Risk Parity Papers

"Generalized Risk-Based Investing" *Emmanuel Jurczenko, Thierry Michel and Jerome Teiletche*	SSRN working paper, March 2013
"Risk Parity, Maximum Diversification, and Minimum Variance: An Analytic Perspective" *Roger Clarke, Harindra de Silva and Steven Thorley*	Journal of Portfolio Management, Spring 2013
"Risk Parity Optimality" *Gregg Fisher, Philip Maymin and Zakhar Maymin*	SSRN working paper, March 2013
"Risk without Return" *Lisa Goldberg and Ola Mahmoud*	Journal of Investment Strategies, Spring 2013
"Risk-Factor Diversification and Portfolio Selection" *Scott Pappas, Robert Bianchi, Michael Drew and Rakesh Gupta*	SSRN working paper, August 2012

Source: UBS

Momentum papers

We first review two recent working papers focusing on the causes of momentum drawdowns. Building on the empirical evidence offered by the papers, we implement the proposed strategies that are claimed to improve momentum performance and evaluate their performance across Europe, North America, Pacific Basin ex Japan and Japan.

"Momentum has its Moments", by Pedro Barroso and Pedro Santa-Clara

Momentum has indeed had its moments. The winners-minus-losers strategy suffered dramatic losses of 91.59% between July and August 1932 and 73.42% from March to May 2009, hence rendering momentum quite unappealing to investors with reasonable risk aversion. The objective of this paper is to investigate the reasons for these rare but substantial momentum crashes and to devise a robust risk-managed momentum strategy.

Pedro Barroso and Pedro Santa-Clara make use of Kenneth French's US data library[1] and find that the winner-minus-loser momentum strategy[2] delivers a Sharpe ratio of 0.53 between July 1926 and December 2011, which is the greatest among risk factors (market: 0.39, size: 0.26, value: 0.36). However, this superior performance comes at the expense of significant left tail/crash risk: the skewness and kurtosis of momentum are -2.47 and 18.24, respectively, and are largely driven by the 1932 and 2009 incidents. The question arises: what are the circumstances under which momentum crashes?

Momentum is by construction a strategy with a significant time-varying beta. Following bull markets, winners tend to be high-beta stocks and losers low-beta (if not negative-beta) stocks. Conversely, following bear markets, momentum strategy has a negative beta as it tends to buy low-beta stocks and short high-beta stocks, which have experienced the largest losses in the cross-section (for example, see Grundy and Martin, 2001). The 1932 and 2009 incidents occurred as the market rebounded after the large losses of the Great Depression and the credit crunch, respectively. Following the above, momentum strategy had a negative beta and was therefore dramatically hit by the subsequent market rallies. Could these crashes have been predicted and therefore avoided?

Using daily return data, the authors estimate the risk of the momentum strategy as the 21-day realized volatility and find that is has substantially varied over time, while exhibiting large persistence (serial correlation of 0.70). These features indicate strong risk predictability; indeed, the authors show that the major source of risk predictability is not time-varying market risk, but instead momentum-specific risk. Therefore, a timely risk management scheme applied to the momentum strategy can safeguard against forthcoming drawdowns in high-momentum-risk environments.

The authors suggest scaling the momentum strategy by the 6-month historical realized volatility and targeting the risk of the strategy to a 12% level (see Figure 3). The risk-managed momentum strategy achieves superior performance

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[1] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[2] The momentum portfolios are constructed using all stocks listed on NYSE/NASDAQ/AMEX based on prior 12-month -skipping last month- return NYSE decile breakpoints.

compared to the ordinary strategy and effectively eliminates the 1932 and 2009 crashes (see Figure 4). It delivers a Sharpe ratio of 0.93 (almost doubling the 0.53 of the standard momentum strategy), with skewness of -0.42 (down from -2.47) and kurtosis of 2.68 (down from 18.24). Crash risk is largely reduced and the risk-managed strategy no longer has variable and persistent risk.

The benefits from managing the risk of momentum are not limited to the 1932 and 2009 incidents. Over the period January 1945 - December 2005, risk managing the momentum strategy increases the Sharpe ratio from 0.86 to 1.12 and reduces the skewness from -0.91 to -0.17 and the kurtosis from 6.0 to 1.2. Finally, the effects are shown to be pervasive in international markets. Between July 1980 and October 2011, the strategy's Sharpe ratio significantly increases in France (from 0.63 to 1.03), in Germany (from 1.02 to 1.39), in the UK (from 1.09 to 1.77) and even in Japan, which has historically exhibited no momentum patterns (from 0.08 to 0.24).

Figure 3: Weight of risk-managed momentum portfolio
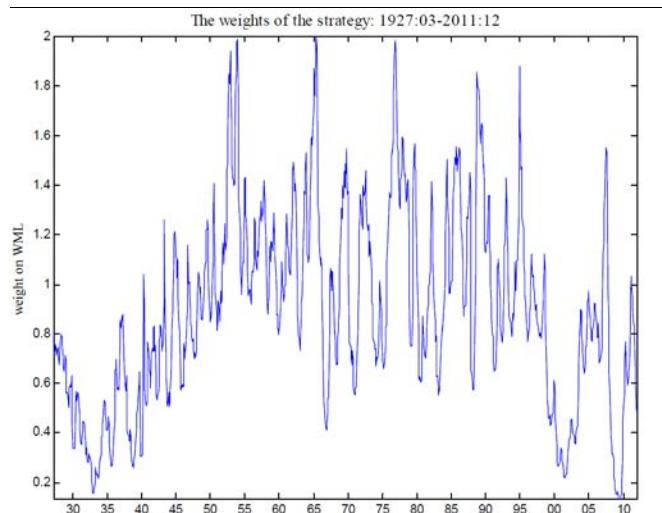
Source: "*Momentum has its Moments*" by P. Barroso and P. Santa-Clara; Figure 8, reproduced with permission. The weight of the risk-managed momentum strategy is defined as the ratio of the target volatility (12%) and the realized volatility over the previous 6 months.

Figure 4: Cumulative returns
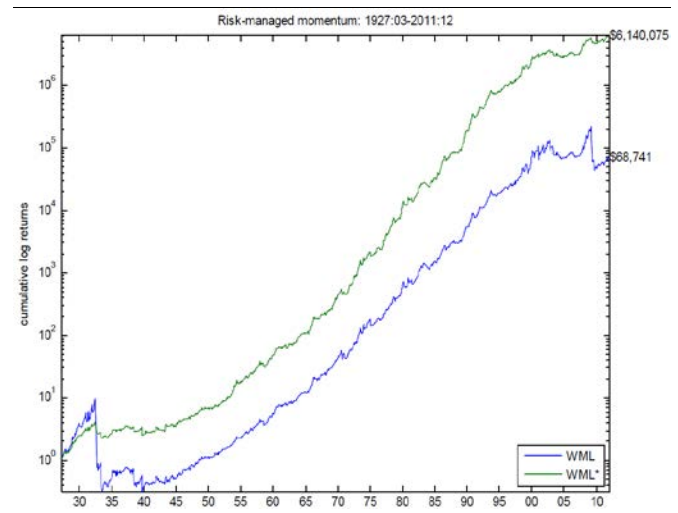
Source: "*Momentum has its Moments*" by P. Barroso and P. Santa-Clara; Figure 5, reproduced with permission. The figure presents the cumulative returns of the standard winner-minus-loser momentum strategy ("WML") and the risk-managed (constant-volatility) momentum strategy proposed by the authors ("WML*") with 12% target volatility.

"Momentum Crashes", by Kent Daniel and Tobias Moskowitz

As already discussed in the previous paper review ("*Momentum has its Moments*" by P. Barroso and P. Santa-Clara), the standard winner-minus-loser momentum strategy suffers dramatic losses when the market rebounds after a period of market distress. The suggested way to alleviate the heavily skewed momentum returns is to manage the risk of the strategy by targeting a constant level of volatility. Kent Daniel and Tobias Moskowitz take the analysis one step further. They analyse in detail the reasons for momentum crashes and suggest more robust ways of risk-managing the momentum portfolio by incorporating return forecasts (rather than just targeting the volatility of the strategy).

Going back to the largest historical momentum crashes, during July and August 1932, past winners earned 30%, whereas past losers earned 236%. The respective returns for the period March to May 2009 were 6.5% versus 156%. These patterns suggest that it could very well be the time-varying beta of the strategy that is driving these momentum crashes. Using the CRSP (NYSE/NASDAQ/AMEX) dataset for the period between January 1927 and December 2010, the authors estimate the difference between up and down market betas for the past winner and loser portfolios during bear markets (defined by a negative past two-year return for the CRSP value-weighted index). Past losers' up beta is greater than their down beta by 0.61 during bear markets (2.12 versus 1.52). On the contrary, the winner portfolio's up beta is, in fact, lower than the down beta by 0.21 (0.65 versus 0.86). As a consequence, following bear markets when stock prices rally, the winner-minus-loser portfolio has a largely significant negative up beta of -1.47. This negative up beta is almost entirely driven by the loser decile, and is one reason for momentum experiencing substantial losses. It is worth noting that no significant patterns between up and down betas exist during bull periods.

These asymmetric effects give rise to an option-like behaviour for past losers and therefore for the momentum portfolio, which looks like a short call option on the market in panic states and, therefore, like a "short volatility" position. Along these lines, the authors argue that the value of the option is not reflected in the prices of the past losers and that the value of the option should be a function of future market volatility. They find that realised market variance and a bear market indicator can independently forecast future momentum returns.

Given these empirical findings, they suggest a dynamic adjustment scheme for the standard momentum strategy that incorporates forecasts of both the return and the volatility of the strategy. In essence, the weight of the strategy is defined so that the Sharpe ratio of the strategy is maximised and it is shown to be proportional to the expected momentum returns over the next period and inversely proportional to the conditional variance of the returns. If the forecast mean return was always proportional to the forecast volatility, then the strategy's Sharpe ratio would be time-invariant and the optimal dynamic weighting scheme would reduce to a constant volatility weighting scheme like the one suggested in "*Momentum has its Moments*". Nevertheless, momentum returns are shown to be slightly negatively related to the forecast volatility: in states of high-momentum volatility, average momentum returns are low. Following that, the dynamic momentum strategy is shown to outperform not only the standard momentum strategy, but also the constant volatility momentum strategy (see Figure 5). In the periods January 1927 and September 2012, the Sharpe ratios of the three momentum strategies are: standard strategy 0.52, constant volatility strategy 0.92, and dynamic strategy 1.10. The performance ranking is robust across various sub-periods.

Finally, extending the analysis outside the US and across asset classes, the authors show that the asymmetric beta effects in bear markets are pervasive. They document lower returns following bear markets for equity momentum strategies in Europe, Japan and UK, as well as for momentum strategies formed using commodity futures, currencies or country equity market indices.

Figure 5: Cumulative Returns of Standard, Constant-Vol. and Dynamic Momentum
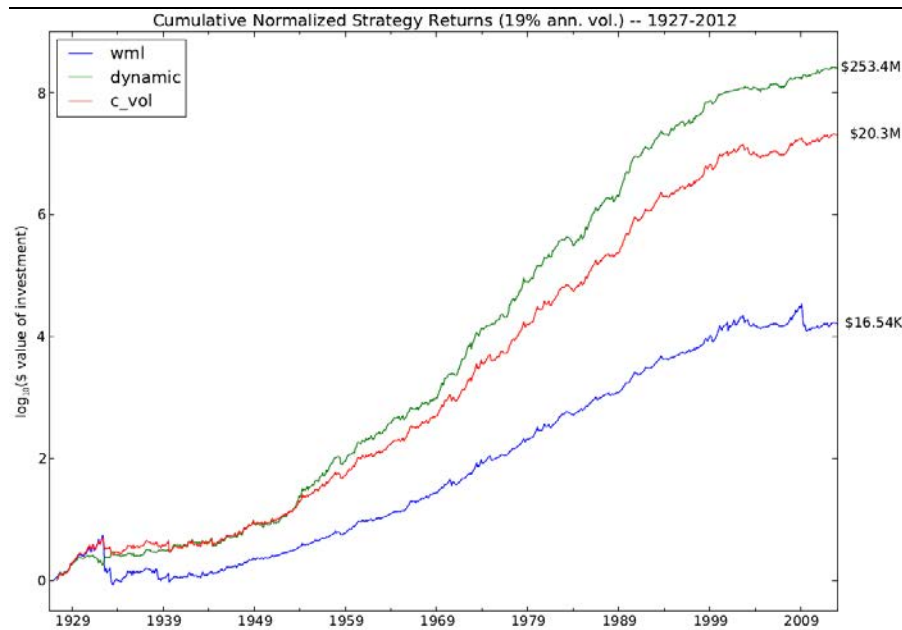
Source: "*Momentum Crashes*" by K. Daniel and T. Moskowitz; Figure 9, reproduced with permission. The figure presents the cumulative returns of the standard winner-minus-loser momentum strategy ("wml"), the constant-volatility momentum strategy ("c_vol") with 19% target volatility and the dynamic strategy proposed by the authors ("dynamic") also with 19% target volatility.

Does the approach work elsewhere?

The approach in the paper was developed using the CRSP data over a long horizon. We have attempted to reproduce the strategy in North America, Europe, Japan and Pacific Basin ex Japan using the UBS 12-month price momentum style indices as shown in our monthly *Global Style Watch* publication. These indices are based on the Dow Jones World Indices. For details of their composition please see the back of the *Global Style Watch* report.

We compare three strategies for each region: a winners-minus-losers portfolio (i.e. long the high momentum index, short the low momentum index), a volatility targeted version of this portfolio where we aim for a constant volatility of 15% for the momentum strategy and a dynamically weighted approach where we use the regression from the paper to forecast the returns to the portfolio:

$$\hat{\mu}_{WML,t} = \gamma_0 + \gamma_{int} I_B \sigma_{m,t}$$

where I_B is a bear market indicator (1 if the market fell over the preceding 24 months, 0 otherwise) and $\sigma_{m,t}$ is the ex-ante estimator of the market volatility. For both the market and momentum volatility estimates we chose to use the realised volatility measured using 22 daily returns[3].

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[3] A simplification over the paper, which uses a combination of 22, 63 and 126 day estimators to forecast volatility.

For the constant volatility strategy, the weight in the momentum portfolio is $w_t^{CV} = 15\%/\sigma_{WML,t}$ whereas for the dynamic strategy the weight is given by $w_t^{DYN} = (1/2\lambda)\hat{\mu}_{WML,t}/\sigma_{WML,t}^2$. Constant λ is chosen to set the volatility of the dynamic strategy over the period to be similar to that of the underlying index. We re-estimate the forecast regression and hence the weights each month.

Figure 6: Performance of momentum timing strategies in Europe
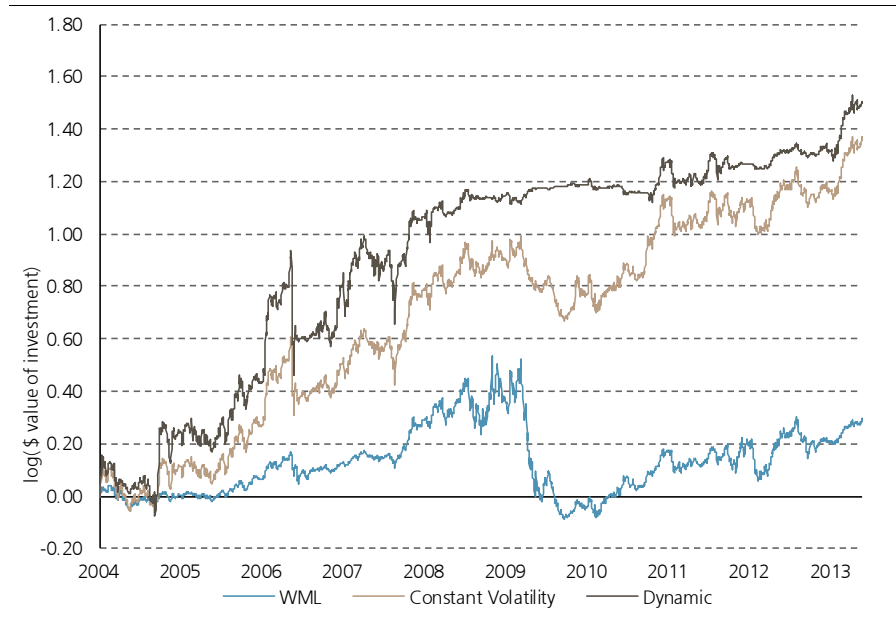
Source: UBS

Figure 6 shows the cumulative returns of the three strategies in Europe over the period 31st December 2003 to 17th May 2013. The respective Sharpe ratios are 0.20, 0.83 and 0.88. One benefit of the dynamic strategy is that it has almost no exposure to momentum from mid-2008 to mid-2010 in Europe. Figure 7 summarises the results for our four regions. In all but Japan, the dynamic strategy has a higher Sharpe ratio than the simple volatility targeted portfolio.

Figure 7: Sharpe ratios of WML, vol-targeted and dynamic momentum strategies

	Momentum	Volatility Targeted	Dynamic
Europe	0.20	0.83	0.88
North America	-0.03	0.37	0.50
Pacific Basin ex Japan	0.33	0.95	1.19
Japan	-0.03	0.4	0.35

Source: UBS

Risk parity papers

The second part of our Academic Research monitor summarises the findings of a list of recent papers focusing on risk-based portfolio construction methodologies.

At this stage, it is worth noting that there exist two definitions of "*risk parity*" used by the papers. While most papers define risk parity as the portfolio weighting scheme that makes the contributions to risk of each asset equal (i.e. taking into account the correlations between the assets as well as their risk – also known as the Equal Risk Contribution (ERC) portfolio), Gregg *et al.* (2013) define risk parity as the simple weighting of the assets in a portfolio by the inverse of their volatilities – effectively running a volatility targeting on each asset individually.

"Generalized Risk-Based Investing" by Emmanuel Jurczenko, Thierry Michel and Jerome Teiletche

 and

"Risk Parity, Maximum Diversification, and Minimum Variance: An Analytic Perspective" by Roger Clarke, Harindra de Silva and Steven Thorley

These two papers are jointly reviewed as they cover fairly similar topics and employ similar methodologies. In particular, they aim to provide a more rigorous and theoretical analysis of risk-based strategies, rather than an empirical analysis. Interestingly, Emmanuel Jurczenko, Thierry Michel and Jerome Teiletche show that (i) minimum variance, (ii) maximum diversification, (iii) equal weighting and (iv) risk parity portfolio weighting schemes are all special cases of a generic function, which has two specific parameters that the authors describe as a regularization parameter and a risk tolerance level coefficient.

If we define σ_P as the standard deviation of the portfolio, σ_i as the standard deviation of an asset and $\sigma_{i,j}$ as the covariance between two assets, then the marginal risk contribution of asset *i* is

$$MRC_i = \frac{\partial \sigma_P}{\partial w_i} = \frac{\sigma_{i,P}}{\sigma_P}$$

where $\sigma_{i,P} = \sum_j w_j \sigma_{i,j}$ is the covariance of the ith asset with the portfolio. The total risk contribution of this i^{th} asset is therefore $TRC_i = w_i \times MRC_i$ and the portfolio risk is then trivially the sum of these total risk contributions.

The authors of "*Generalised Risk-Based Investing*" then set out a general problem for the risk-based portfolio construction, which they show has the general solution:

$$\frac{w_i^\gamma}{\sigma_i^\delta} \times MRC_i = \frac{w_j^\gamma}{\sigma_j^\delta} \times MRC_j = \tau \quad \forall(i,j)$$

The four common risk-based strategies are then defined by the choice of the two parameters gamma and delta: minimum variance has (0, 0), maximum diversification has (0, 1), risk parity (1, 0) and equal weighting (infinity, 0); see for more details. However, as the authors note, these parameters are only four specific cases of a wider set of risk-based strategies.

Interpreting these two parameters, gamma determines the sensitivity to volatility and correlation estimates; the lower the gamma, the more sensitive the solution is to these estimates. Also, as gamma increases, the problem of duplicate assets arises – if there are two identical assets, then risk parity and equal weighting will change their respective allocations, which doesn't seem sensible. Delta is the sensitivity to individual risk estimates. As delta increases, the sensitivity to these individual risk estimates falls. This implies that the minimum variance portfolio has lower tolerance for high-risk assets than maximum diversification (all else being equal). As delta tends to infinity, then the solution portfolio will tend to the most risky asset.

The paper then goes on to discuss the uniqueness and existence of solutions to this general optimisation problem, and then the conditions for each of the four special cases to be optimal. Their conclusions are summarised in Figure 8 below, along with other properties/ features of the risk-based portfolios.

Both papers give analytic solutions for the three non-trivial cases (equal weighting being rather obvious) and in particular use the solution for the single factor (CAPM) case to show the properties of the solution portfolios. They also provide solutions for the multi-factor risk model case.

Both papers then run large-scale examples, using either the constituents of the MSCI World (Jurczenko *et al.*) or the largest 1,000 names in the CRSP database (Clarke *et al.*) and use these to illustrate the properties and behaviours of the three fund types.

Figure 8: Risk-Based Investing - Summary

Portfolio	Strategy definition	Optimality conditions	Capital / risk distribution	Risk characteristics
MV (0, 0)	Equalises MRC_i	Identical excess returns	Highly concentrated Highly sensitive to *VCV* High turnover	Lowest risk Lowest beta High TE
MD (0, 1)	Equalises volatility-scaled MRC_i	Identical Sharpe ratios	Highly concentrated Highly sensitive to correlations Moderately sensitive to vols High turnover	Low / medium risk Low beta High TE
RP (1, 0)	Equalises TRC_i	Identical Sharpe ratios Unique correlation	Diversified in risk Moderately sensitive to *VCV* Medium turnover	Medium risk Beta below but close to 1 Medium TE
EW (∞, 0)	Equalises w_i	Identical excess returns Identical volatilities Unique correlation	Diversified in capital Insensitive to *VCV* Low turnover	Medium to high total risk Low / Medium specific risk Beta above but close to 1 Low / medium TE

Source: *"Generalised Risk-Based Investing"* by Emmanuel Jurczenko, Thierry Michel and Jerome Teiletche; Table 3, reproduced with permission. The table summarises the different risk-based strategies based on the choice of the parameters gamma and delta. *VCV* denotes the covariance matrix, MRC_i denotes the marginal risk contribution, TRC_i denotes the total risk contribution and w_i denotes ith asset's weight.

"Risk Parity Optimality" by Gregg Fisher, Philip Maymin and Zakhar Maymin

In this paper, Gregg Fisher, Philip Maymin and Zakhar Maymin aim to answer the question of when risk parity (note that they define risk parity as simply weighting by the inverse of volatility) is an optimal strategy for constructing a portfolio. They give two results: (a) the *"probability of risk parity beating any other portfolio is more than 50%"* and (b) the risk parity portfolio will *"under some natural assumptions, [...] do better than any other portfolio construction method under the worst possible combination of true expected returns"*.

The authors also identify two cases where the minimum Sharpe ratio of the risk parity portfolio is greater than the minimum Sharpe ratio of any other portfolio. The first case is when the Sharpe ratio of each asset is greater than some positive constant and all correlations between the assets are less than some constant and strictly less than 1. The second case is when the sum of all the assets' Sharpe ratios is greater than some positive constant (individual assets may have negative Sharpe ratios, but their sum must be positive).

The final result in the paper shows that for *"a positive constant correlation matrix, assuming that the assets' future positive Sharpe ratios are chosen at random"*, the probability that the risk parity portfolio has a better Sharpe ratio than any other portfolio is greater than 50%.

We find the paper interesting in that it attempts to give some theoretical support to the risk-parity heuristic. However, for an equity portfolio, the assumption that all Sharpe ratios are positive (or even sum up to a positive total) does seem somewhat unlikely to us, perhaps contrary to what might be the case for general asset allocation, and, therefore, we wonder about the general applicability of the result.

"Risk without Return" by Lisa Goldberg and Ola Mahmoud

In this short note, Lisa Goldberg and Ola Mahmoud compare three risk-based strategies for asset allocation with equal weighted balanced approaches. They use four assets in their baskets: US equities, US treasury bonds, US corporate bonds and commodities, with data from January 1988 to December 2010. In a backtest, they show that all three risk-based approaches have higher Sharpe ratios than the balanced or equally-weighted portfolios. The balanced portfolio has the highest return, but also the highest risk and therefore the lowest Sharpe ratio.

They make four observations that investors should be aware of. Firstly, all three risk-based approaches are *"manifestations of a single effect"* (something shown theoretically in Clarke *et al.*, 2011), with the empirical correlations between the three risk-based approaches being around 0.9. Secondly, the risk-based approaches can have high turnover, which, depending on the assumptions on costs, can reduce the benefits of the approaches quite significantly. The minimum variance strategy, in particular, exhibits very high concentration risk, whereas the risk parity strategy is reasonably well-diversified.

Thirdly, they introduce the so-called *risk diversification index*, as a risk-based parallel to the Herfindahl-Hirschman index, which measures concentration risk. Their final observation is that the risk parity strategy is diversified in both weight and risk terms, and this might explain why the risk parity strategy had the best performance in their study.

"Risk-Factor Diversification and Portfolio Selection" by Scott Pappas, Robert Bianchi, Michael Drew and Rakesh Gupta

Most approaches and back tests of risk parity and equivalent strategies focus on allocating risk between asset classes or individual assets. There is, however, a different approach, which looks to allocate between the underlying risk factors. This paper conducts a long-term analysis of this approach and concludes that "the outperformance of risk-factor diversification over asset-class diversification may not be as conclusive as previously presented."

The first question the authors address is that of which risk factors to select. Given that they are aiming to "analyse the performance of risk-factors over multiple market cycles" and to "simplify and generalise the portfolio construction process", they choose five risk factors: market, size, value, credit, and term risk-factors (the first three coming from Ken French's web site, the latter two based on the Barclays bond indices).

All chosen factors have positive risk premia over the period 1973 to 2011, ranging from 5.63% per annum for the stock market to 44 basis points per annum for the credit spread.

The authors contrast a number of portfolio construction techniques: mean-variance and minimum variance (with and without short sale constraints), together with equal weighting and equal risk weighting. As is common in this literature, the forecast returns are calculated as the sample means, in this case using 60 months of history. The comparison is made between allocation across assets (namely bonds and equities) and allocation across the five risk factors.

Reviewing the in- and out-of-sample results, they find that the differences in Sharpe ratios between the different techniques are generally not significant, or of marginal significance, and (as shown in Anderson, Bianchi and Goldberg, 2012) the relative performance between the techniques is dependent on the time period: conducting the analysis over a longer time frame than previous work shows that "the most recent past had been a favourable period for risk-factor diversification."

They find that the minimum variance approach is particularly disadvantaged in that it tends to have a very large exposure to the credit risk factor (which is very low risk but also low return): ignoring the size of the risk premium appears disadvantageous in this case.

The final lesson from the paper is that the choice of risk factors has a significant effect on the performance of different risk-based strategies. Factors with very low risk in comparison to the other factors will end up with a large weighting in the final portfolio, irrespective of the size (or sign) of their risk premia. We note that the same holds for the choice of assets.

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UBS 12-Month Rating	Definition	Coverage[1]	IB Services[2]
Buy	FSR is > 6% above the MRA.	46%	35%
Neutral	FSR is between -6% and 6% of the MRA.	44%	37%
Sell	FSR is > 6% below the MRA.	10%	21%
UBS Short-Term Rating	Definition	Coverage[3]	IB Services[4]
Buy	Stock price expected to rise within three months from the time the rating was assigned because of a specific catalyst or event.	less than 1%	33%
Sell	Stock price expected to fall within three months from the time the rating was assigned because of a specific catalyst or event.	less than 1%	20%

Source: UBS. Rating allocations are as of 30 June 2013.
1: Percentage of companies under coverage globally within the 12-month rating category. 2: Percentage of companies within the 12-month rating category for which investment banking (IB) services were provided within the past 12 months.
3: Percentage of companies under coverage globally within the Short-Term rating category. 4: Percentage of companies within the Short-Term rating category for which investment banking (IB) services were provided within the past 12 months.

KEY DEFINITIONS: Forecast Stock Return (FSR) is defined as expected percentage price appreciation plus gross dividend yield over the next 12 months. **Market Return Assumption (MRA)** is defined as the one-year local market interest rate plus 5% (a proxy for, and not a forecast of, the equity risk premium). **Under Review (UR)** Stocks may be flagged as UR by the analyst, indicating that the stock's price target and/or rating are subject to possible change in the near term, usually in response to an event that may affect the investment case or valuation. **Short-Term Ratings** reflect the expected near-term (up to three months) performance of the stock and do not reflect any change in the fundamental view or investment case. **Equity Price Targets** have an investment horizon of 12 months.

EXCEPTIONS AND SPECIAL CASES: UK and European Investment Fund ratings and definitions are: Buy: Positive on factors such as structure, management, performance record, discount; **Neutral:** Neutral on factors such as structure, management, performance record, discount; **Sell:** Negative on factors such as structure, management, performance record, discount. **Core Banding Exceptions (CBE):** Exceptions to the standard +/-6% bands may be granted by the Investment Review Committee (IRC). Factors considered by the IRC include the stock's volatility and the credit spread of the respective company's debt. As a result, stocks deemed to be very high or low risk may be subject to higher or lower bands as they relate to the rating. When such exceptions apply, they will be identified in the Company Disclosures table in the relevant research piece.

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Unless otherwise indicated, please refer to the Valuation and Risk sections within the body of this report.

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