Risk Parity Strategies For Equity Portfolio Management

Can an asset-class strategy translate to equities?

By Frank Siu
Risk-based strategies have gained popularity amid market uncertainty, and many are now being touted as “smart beta,” providing a systematic way to outperform traditional capitalization-weighted benchmarks. Here we examine the notion of risk parity, taking what has almost exclusively been discussed in an asset allocation context and applying its concepts to equity-only portfolio construction.

Risk parity seeks to equalize sources of risk such that the relative marginal contribution to risk (RMCTR) from each source is equal. Historically, research has treated asset classes as the sources of risk, because these are typically quite distinct and relatively uncorrelated (for example, interest rate versus equity market risk). Given an \( n \)-vector of loadings on sources of risk \( W \) and their covariance matrix \( Q \), a risk parity portfolio satisfies:

\[
\frac{w_i(Qw)_i}{w^T Qw} = \frac{w_j(Qw)_j}{w^T Qw} \quad \forall i, j = 1 \ldots n \quad (1)
\]

In a traditional asset allocation setting where \( n \) represents the number of asset classes, \( n \) is “small” (<10), and this problem is easy to solve, even using odd formulations and mediocre solvers. In equity portfolios, \( n \) is usually larger, and the sources of risk may be individual stocks, groupings of stocks (sectors, countries, regions or combinations thereof) or quantitative risk factors. By modeling risk parity as a set of optimization constraints, we are able to find risk-parity portfolios efficiently for large \( n \). In addition, we will demonstrate how certain formulations of risk parity can in fact be used as an overlay on top of an existing investment process. The following discussion is divided into three parts. We begin with the simplest case, where the elements of \( w \) represent individual stocks, so each stock constitutes a source of risk (dubbed “asset risk parity” henceforth). Next, the analysis will expand to include risk parity between groupings of stocks (such as country/sector). Finally, we introduce the idea of risk parity between risk factors.

Rather than presenting a series of backtests with the goal of promoting risk-parity strategies and validating their possible superior performance, we discuss methods for constructing risk-parity portfolios and analyze how each variant of risk parity affects the resulting portfolio composition.

Constructing Asset Risk-Parity Portfolios

Despite its straightforward definition and prevalence in research, there is little discussion—let alone consensus—on exactly how risk-parity portfolios are built. Methods discussed include model simplification (e.g., ignoring correlations, per Anderson et al. (2012)), ad-hoc/trial-and-error approaches using rudimentary statistical software (Kazemi, 2012) and iterative numerical algorithms (Chaves et al. 2012). Finding a portfolio that satisfies Equation 1 is sometimes tackled by using a non-linear optimizer to minimize a loss function measuring the portfolio’s deviation from risk parity, for example, the sum of squared differences between stocks’ RMCTRs, as in Maillard et al. (2010):

\[
w = \arg \min_w \sum_{i=1}^n \sum_{j=1}^n \left( \frac{w_i (Qw)_i}{w^T Qw} - \frac{w_j (Qw)_j}{w^T Qw} \right)^2 \quad \forall i \neq j \quad (2)
\]

In the equity world where \( n \) is typically large, contrary to this conventional method, it is preferable to model risk parity as optimization constraints. In the case of a long-only portfolio where \( w \) represents individual stock weights, Equation 1 can be expressed as a set of convex constraints on the RMCTR of each stock:

\[
\frac{w^T \Lambda_i Qw}{w^T Qw} \geq \frac{1}{n} \quad \forall i \quad (3)
\]

Here, \( \Lambda \) is a diagonal matrix with \( \Lambda_{ii} = 1 \) and zero elsewhere, and \( n \) represents the total number of stocks. Equation 3 can be formulated and solved as a convex optimization problem. Additionally, when minimizing risk-parity violations using the objective function, per Equation 2, depending on the quality of the search algorithm, one may end up with portfolios that are in fact not risk parity but have simply exhausted that particular optimizer’s ability to find a better solution. Finally, minimizing departure from risk parity is dangerous because depending on the loss function, it may be difficult to differentiate between large violations involving a few stocks and small violations across the board.

Kaya and Lee (2012) express risk parity as the solution to a utility maximization problem and show that in a long-only and fully invested setting, there exists a unique set of weights \( w \) that satisfies Equation 1. This result only applies to asset risk parity in this restricted case; such a claim cannot be made for risk parity between groupings of stocks or risk factors, where the mathematics of finding a solution are far more complex and are discussed later. Moreover, if additional constraints are imposed, the problem may sometimes not have a solution at all. Nevertheless, establishing uniqueness is of paramount importance because it suggests that asset risk parity fully defines a portfolio strategy. As a set of portfolio constraints, asset risk-parity is akin to a weighting scheme: It contains the necessary and sufficient information for uniquely specifying the final portfolio composition.

Asset Risk Parity In ‘Small’ Blue Chip Universes

If uniqueness is established, the constraints in Equation 3 can be combined with any objective function to yield the same solution. In the following examples, we use a “minimize variance” objective. Figure 1 shows the performance of such an implementation of asset-risk parity, applied to various benchmark universes, with generally positive results. *Asset-risk parity seems well suited to blue chip benchmark universes containing relatively small numbers of names, where there is typically concentration risk that can be diversified.* Of particular interest is the relatively manageable
turnover (figures are annualized one-way) when compared with other risk-based strategies. In most cases, risk parity achieves diversification by down-weighting mega-cap names with very large weights, resulting in a slight low-beta tilt; Kaya and Lee (2012) provide an analytical proof of why this is so. Risk reduction compared with the capitalization-weighted benchmark is present but to a lesser extent than, say, minimum-variance strategies, where aggressive low-volatility positioning often results in high tracking error, a form of “risk” some investors find difficult to accept.

**Asset Risk Parity In Broad-Market Universes**
Moving to broader benchmark universes, the optimization problem becomes more difficult, because both the number of constraints and the dimensionality of each constraint increases. Furthermore, the risk profile of the strategy becomes increasingly dependent on benchmark construction and market structure, due to the implicit requirement that every stock be held. To illustrate, consider applying asset-risk parity to the Euro Stoxx 50 and the Euro Stoxx (~300 names) universes. Their corresponding ex-ante tracking error decompositions are presented in Figures 2a and 2b.

There are large differences between the risk profiles of the two portfolios. In the full Euro Stoxx universe, roughly two-thirds of names are mid- and small-caps. Maintaining risk parity will systematically overweight many such names, resulting in a large risk contribution from the small size bias (the red area in Figure 2b), whose share of risk in the Euro Stoxx 50 case was almost zero. Similarly, significant underweighting of the largest blue chip names creates large negative-beta and low-volatility tilts. Figure 3 shows the relationship between the number of names in the universe.
and the resulting risk breakdown as well as portfolio beta. To summarize, by increasing universe breadth, the drivers of risk/return shift disproportionately toward systematic risk factors rather than stock-level differences vis-à-vis the benchmark as a result of “reshuffling” weights to comply with risk parity. When the universe becomes very broad, such as in Figure 2b, the portfolio risk profile approaches that of a low-beta, small-cap strategy. Increasing universe size may not necessarily detract from returns, but changes the investment thesis considerably. Returns become “polluted” by factor effects; most notably, low beta and small size dominate the strategy’s exposure profile, dwarfing the effects from risk diversification. Figure 4 shows the risk and performance of asset-risk parity applied to several large-cap benchmark universes from the previous section compared with their broad-market equivalent. The backtested results are consistent with the trends illustrated in Figure 3—asset-risk parity in large universes is characterized by overweighting small-cap stocks and a substantial portion of return arising from low-beta positioning. These two factor bets are largely responsible for increased tracking error, which in turn results in inferior risk-adjusted active returns.

**Risk Parity Over Groupings Of Stocks**

In the previous example of asset-risk parity on the Euro Stoxx 50, risk was not being diversified across 50 independent sources; in fact, as Figures 5A and 5B show, there is still considerable concentration along sector and country lines. More generally, in any long-only equity-only portfolio, the broad market (beta) accounts for a large portion of risk, and stocks in the same sector or country remain highly correlated.

An alternative to asset-risk parity may be to equalize over systematic sources of risk, such as sectors or countries. For global investment universes, the presence of some very small countries renders country risk parity somewhat impractical, and sectors may not be homogeneous across geographies; hence, one could consider region-sector groupings, such as Asian technology, European banks, etc. In general, risk parity over groupings of stocks can be expressed mathematically by summing up Equation 3 over all stocks in a subset S:

\[
\sum_{i \in S} \frac{w^T A_i q w}{w^T Q w} \geq \frac{1}{m}
\]

(4)

Here, \( m \) represents the number of groupings \( S \). Despite the similarity of Equation 4 to the asset-risk parity case of

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**Figure 4**

**Performance Of Asset Risk Parity Strategies In Select Markets, Quarterly Backtest, 2005-2013**

<table>
<thead>
<tr>
<th>Source: Axioma, Stoxx, Thomson Reuters</th>
</tr>
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<tbody>
<tr>
<td><strong>Note</strong>: Using monthly gross returns in EUR (CHF for SMI). Risk and return figures are annualized. * The CAC All-Tradable replaced the SBF 250 in early 2011.</td>
</tr>
</tbody>
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**Figure 3**

**Effect Of Universe Breadth On Average Factor And Specific Contributions To Tracking Error**

Source: Axioma

**Note**: Quarterly backtest using pan-European universe, 2005 to 2013

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Sources: Axioma, Stoxx, Thomson Reuters

**Note**: Using monthly gross returns in EUR (CHF for SMI). Risk and return figures are annualized. * The CAC All-Tradable replaced the SBF 250 in early 2011.
Equation 3, the problem is continuous nonconvex, therefore significantly more difficult to solve. Optimality cannot be guaranteed and neither can the existence of a unique solution. Solution quality and the mere ability to find feasible solutions will depend heavily on the numerical techniques employed by one’s solver. As such, the advantages of enforcing parity via optimization constraints rather than the objective function become apparent. (Note also that the number of names is free to vary, no longer dictated by the breadth of the universe.) Given such complexities in implementing the optimization, some practitioners may opt to construct portfolios by trial and error, perhaps starting with the capitalization-weighted benchmark and manually adjusting allocations to the groupings in an ad hoc fashion until all their risk contributions fall into the same “ballpark.” Chaves et al. (2012) proposes numerical algorithms for computing risk-parity portfolios, but it remains unclear how or whether such methods can be adapted to groupings of stocks where the number of names held can vary.

In the following examples, we solve the problem heuristically and are generally able to find solutions that satisfy, or come very close to, risk parity. Occasionally, the optimizer fails to find a solution, usually in small universes where some groupings are sparsely populated, thereby not providing sufficient choices for diversification. Equally problematic are small sectors or countries entering and leaving the universe, inducing additional turnover as well as instability in the relative marginal risk contribution share of the remaining groupings present. In many cases, reducing the right-hand side of Equation 4 by a tiny ε is sufficient to yield a solution, though one or more groupings may be marginally out of parity. Having an ample pool of stocks to choose from is thus helpful in ensuring a solution. In contrast to asset risk parity, which is best suited to concentrated universes with few names, risk parity of groupings with other portfolio construction rules, trading or deviation from a benchmark index. This is especially important in risk parity over groupings where solution uniqueness cannot be established; in these cases, minimizing violations of risk parity between groupings alone is not sufficient for producing an attractive investment portfolio. Consider the trivial example where we select one stock at random from each sector and apply asset risk parity to the portfolio—this solution satisfies sector risk parity but is unlikely to have any real-world appeal.

Figure 6 contains several examples of combining risk parity of groupings with other portfolio construction rules, again using the Euro Stoxx universe. By changing the optimization objective and/or applying additional constraints, we are able to obtain significantly different performance. In particular, note the differences in risk, beta, name count and turnover. While other risk-based strategies are often accompanied by large deviations from the capitalization-weighted benchmark, here it appears that sector risk parity can be achieved with a surprisingly small tracking error budget (about 2 percent). We leave it to readers to experiment with additional permutations; for example, constraining risk factor exposures, imposing holdings constraints or even incorporating an expected returns (alpha) objective.

In Bai et al. (2013), risk parity over sector groupings is solved the conventional way—by minimizing an objective function encapsulating total violations of risk parity—but it is unclear what properties the optimal portfolio satisfies, apart from exhibiting sector risk parity. For example, all three portfolios in Figure 6 are optimal under their formulation, but the user has no control over which variant is returned as the solution.

In short, risk parity over groupings of stocks is a complex problem and requires careful research and calibration of optimization parameters to the particular investment goal and universe. Figure 7 shows two different solutions to sector risk parity; both allocate risk equally across sectors but pursue radically different investment objectives—Figure 7a uses sector risk parity in conjunction with a minimum variance strategy, and Figure 7b applies sector risk parity to a passive indexing strategy. We reiterate and summarize thusly: Asset risk parity has a unique solution and fully
defines a portfolio strategy; risk parity over groupings of stocks, on the other hand, is a risk control component of a larger overall strategy. Previously, researchers may not have had adequately flexible tools to separate risk-parity requirements from the optimization objective; hence, this notion of using risk parity as an “overlay” has largely gone unexplored.

Factor Risk Parity

Let us begin with a factor risk model that decomposes risk (the asset-asset covariance matrix $Q$) into common factor and stock-specific components:

$$Q = X\Omega X^T + \Delta \quad (5)$$

$X$ is a matrix of factor exposures, $\Omega$ is the factor covariance matrix and $\Delta$ is the diagonal matrix of stock-specific variances. Let $f = Xw$ be the factor exposures of a portfolio $w$. Suppose the exposure matrix $X$ is made up of a set of country, industry and style factors:

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The factor covariance matrix can be divided into blocks corresponding to factor types/groups:

$$\Omega = \begin{bmatrix} \Omega_{CC} & \Omega_{CI} & \Omega_{CS} \\ \Omega_{IC} & \Omega_{II} & \Omega_{IS} \\ \Omega_{SC} & \Omega_{SI} & \Omega_{SS} \end{bmatrix}$$

We can enforce risk parity across the set of country risk factors by:

$$\frac{f_i^T \Lambda_i \Omega_{cc} f_i}{f_i^T \Omega_{cc} f_i} = \frac{f_j^T \Lambda_j \Omega_{cc} f_j}{f_j^T \Omega_{cc} f_j} \quad \forall i, j \in C \quad (6)$$

Like Equation 3, this can be formulated as a set of convex constraints on relative marginal contribution to risk. A similar condition can be used to implement industry-factor risk parity. Other factors, such as those of Fama-French-Carhart (Roncalli and Weisang (2012)) or principal components (Lohre et al. (2012)) are also possible, but researchers have noted difficulties with the optimization arising from the fact that exposures to these factors can take on negative values.

Parity across country factors is different from parity across country groupings, described previously, and likewise for industries/sectors. Equation 6 should be interpreted as “ensure the contribution to country risk from each country factor is equal.” Measuring country risk (the denominator in Equation 6) requires under-
The first factor risk-parity portfolio in Figure 8 may appear attractive because of its similarity to benchmark country allocations, but it is questionable whether risk is being diversified in an intuitive or desired manner. Mathematically, Equation 6 is being satisfied, but only in the context of “pure” factors. The second factor risk-parity strategy provides a more egalitarian risk breakdown, but still leaves some puzzling results unresolved. For example, Belgium has one of the highest weights but the lowest risk contribution. Per Figure 9, Belgium has the lowest average levels of stock-specific risk.

**Importance Of Risk Model Specification**

Although a comprehensive discussion of empirical asset pricing and factor risk modeling is beyond the scope of this analysis, we will provide a simple example to illustrate how the portfolio construction implications of Equation 6 depend on nuances pertaining to factor risk model construction. Figure 8 shows country weights and risk contributions from three strategies: The first two use factor risk parity with country factors, and the last one uses risk parity with country groupings.

Furthermore, the first factor risk parity example uses a factor risk model with “pure” country factors, while the second takes the same risk model but embeds broad-market effects into the country factors by means of a linear transformation.

There are large differences in country allocations between the two factor risk-parity strategies even though the risk models used differ only in how they decompose risk by factors. Figure 9 explains this result. France has the lowest “pure” factor volatility; much of its country risk coincides with that of the broad European market. In contrast, Greece’s high risk is largely country-specific, distinct from other core European markets. As a result, if one were to only consider “pure” country factors, Greece would appear almost seven times as risky as France, thus receiving significantly less weight in the first factor risk-parity portfolio. In the second factor risk-parity variant, correlations with the broad market are taken into account, and Greece becomes only twice as risky as France, resulting in less extreme weight differences. The interpretation of risk model factors, therefore, is of vital importance to structure of the factor risk-parity portfolio.

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Equation 6 will only equalize contributions to country factor risk and does not take stock-specific risk into account. Compared with Belgium, other countries claim a larger share of risk owing to their higher average levels of stock-specific risk, despite country factor risk parity having been met. Finally, the third risk-parity portfolio has equal sharing of portfolio risk across countries but involves some very aggressive active country bets.

Additional Interpretations

Recall that Equation 6 seeks to diversify country risk \((f_C^T \Omega_{CC} f_C)\). It is not controlling, contrary to what many may expect, the contribution of country factors to total portfolio risk. Such an interpretation of factor risk parity can be accomplished by:

\[
\frac{f_C^T \Omega_{CC} f_C}{f_C^T f_C} = \frac{f_A^T \Omega_{CC} f_A}{f_A^T f_A} \quad \forall i, j \in C \tag{7}
\]

Risk parity at the factor level allows for a very granular level of risk control but may be too flexible for many users. Without a full understanding of the factor risk model construction process, factor risk parity may yield portfolios that are ultimately inconsistent with the user’s investment needs.

Positioning Versus Other Risk-Based Strategies

Risk parity is often compared with risk-based strategies such as minimum variance or maximum diversification. The first-order condition of a minimum-variance problem requires that the marginal contribution to risk (MCTR) of each stock be equal:

\[
\frac{(Q w)_i}{\sqrt{w^T Q w}} = \frac{(Q w)_j}{\sqrt{w^T Q w}} \quad \forall i, j \tag{8}
\]

Risk parity, on the other hand, equalizes relative MCTR. Maximum diversification and risk parity are both driven by the concept of diversification. Risk parity spreads out risk across its various sources; maximum diversification aims to reduce the share of portfolio risk coming from correlations:

\[
w = \arg \max_w \frac{\sum_i w_i \sigma_i}{\sqrt{w^T Q w}} \tag{9}
\]

The right-hand size of Equation 9 is defined as the “diversification ratio,” and its numerator is equivalent to the risk of a portfolio where all stocks have a correlation of 1. Mathematically, Equation 9 is also analogous to maximizing the Sharpe ratio, where each stock’s expected return is equal to its volatility.

Real-world application of risk-based strategies is often accompanied by investment constraints such as trading limits and restrictions on stock weights or risk exposures, because the unconstrained solution may not be implementable. For example, low-volatility themed strategies typically load heavily on components with low risk and/or low correlation with the market, resulting in concentrated weights, high turnover and sometimes poor liquidity. The performance of these strategies will be very sensitive to choice of constraints and their associated parameters.

Conclusion

We have presented an optimization-based approach to finding risk-parity portfolios that models risk parity as a set of optimization constraints. Compared with the various numerical or analytical methods sometimes discussed in the literature, this approach is scalable, efficient and allows us to analyze different applications of risk parity.

This discussion began by showcasing asset risk parity because, for a given universe of stocks, there is a unique long-only, fully invested portfolio that exhibits asset risk parity. It can be used as an “off the shelf” strategy with no fine-tuning. Unlike many other risk-based strategies, risk parity, by construction, embraces diversification and avoids concentration, offering a high degree of built-in risk and turnover control. Simulated backtests in various markets suggest that asset risk-parity strategies can outperform their corresponding capitalization-weighted benchmarks with reasonable levels of tracking error and trading. The diversification benefits and superior returns make asset risk parity ideal for concentrated benchmark universes comprising relatively few stocks.

Other forms of risk parity can loosely be labeled as principles of portfolio construction and do not alone define a set of portfolio weights. Their applicability, therefore, depends on the other components of the investment strategy. Rather than serving as a risk-based strategy, risk parity over groupings of stocks and factor risk parity are best applied as a form of risk control to augment an existing investment process, preferably on a sufficiently broad universe of stocks.

References