Sources of Return Dispersion in Alternative Risk Premia*

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Abstract

We qualitatively identify eight sources of potential return dispersion across portfolios of risk premia strategies, including strategy inclusion, amount of systematic risk, instrument choices, parameter choices, instrument weighting mechanisms, data choices, execution timing / execution processes, and level of crowding in the strategies employed. We then perform simulation analysis that shows that returns of simulated portfolios can be quite different from one another as a result of altering just a few of these sources of risk premia return dispersion. While others have noted the return dispersion among risk premia providers, our contribution is to provide an initial taxonomy of the drivers of this dispersion as well as an analysis that helps to make these ideas more concrete.

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As alternative risk premia (ARP) strategies become increasingly popular, some increasingly important issues that the industry is grappling with include how to define them, how to compare amongst them, and how to benchmark their returns. Firstly, what, exactly, are risk premia strategies? Given that they are difficult to define, we often find descriptions in industry literature that revolve around their characteristics (low correlation to traditional asset classes, based on sound academic research, wide acceptance, etc.) rather than specific definitions. The definitions we do find commonly read similarly to the one proposed by Anderson and Ellement [2018]: "Focus on systematic exposure to compensated alternative risk premia, such as value, carry, momentum, quality, size, and volatility." While many ARP strategies often have similar descriptions across providers (such as bond carry, or FX value, or equity low volatility), the performance characteristics of risk premia portfolios are often quite different from one another and the correlations between them are often quite low. This heterogeneity can render risk premia funds quite difficult to compare and benchmark. Our goal in this paper is to identify and analyze the likely drivers of these differences, thus facilitating a deeper qualitative understanding of how various risk premia portfolios might be understood, grouped, and compared.

Regan [2017, pps. 3-4] shows that the returns of the risk premia managers in the SG Multi Alternative Risk Premia Index have a remarkably low correlation with one another, with more than two-thirds of the pairwise correlations of the managers in the index coming in at less than 0.4 and an average pairwise correlation of the managers in the index of 0.25. The author notes that "there appears to be a lot of variation in terms of the ultimate implementation of a multi-asset, multi-risk premia strategy."

Suhonen, et al. [2019, p. 20] point to a 0.36 average pairwise correlation during 2018 for the 27 funds they track and a 3-year average pairwise correlation of 0.33 for a smaller sub-set of 12 funds. The authors note [p. 26] that “Without even considering differences in manager resources, experience, and skill sets, given the range of different options and choices starting from the high-level investment philosophy and ‘institutional DNA’ of the manager (e.g. quantitative equity, CTA, multi-asset…), through strategy selection, portfolio construction, and risk management, and all the way to the myriad of possibilities in the exact individual strategy design and trade expression, such diversity should not come as a surprise.”

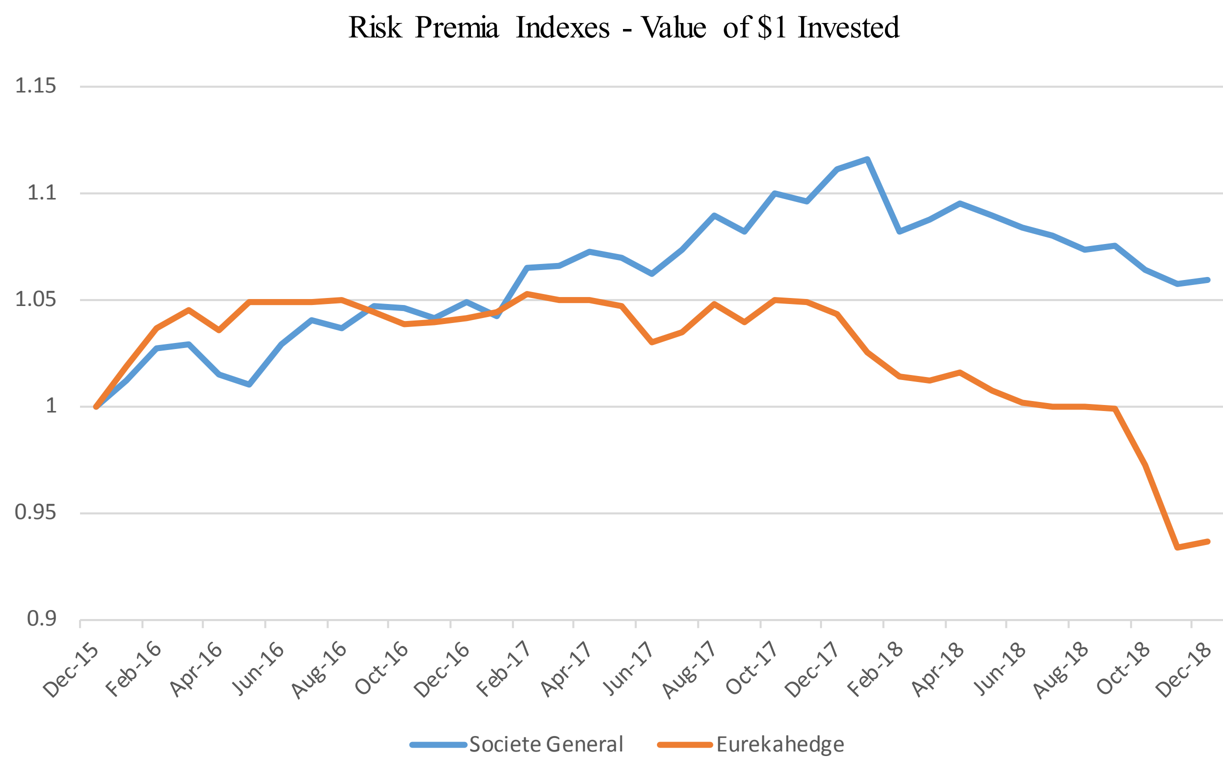
Similarly, Skeggs and Liu [2019, p. 6], in performing analysis on 30 of the largest buy-side risk premia funds, note that “just because two things are similar in name does not mean they have to exhibit similar returns. We demonstrated the importance of understanding factor design and implementation, as differences in these can lead to significant variations, even in well-known risk premia.”

Finally, Aon Hewitt [2017, p. 11] finds that “there is no standard implementation of the ARP strategies discussed above [in their report]. The choice of parameters is at the discretion of the provider. Hence, the same strategy can have wildly different outcomes depending on the construction. Although at face value many of the ARP appear relatively simple, on closer inspection there are a large number of choices to make when implementing a specific strategy. These choices are not only about how to implement specific strategies, but also about how to combine these strategies.”

We argue that implementation can have a substantial impact on the dispersion of returns across risk premia strategies, thus rendering efforts to benchmark and understand the performance of ARP funds more difficult than for other potential fund allocations. Exhibit 1, for example, shows that two of the primary risk premia indices have a correlation with one another of only 0.53 and a return differential after three years (January 2016 to December 2018) of nearly 12%. The correlations are so low and the performance differential so great that one might even question if these indices are trying to capture the same market. Again, we attribute these differences to differences in approach to risk premia investing—to differences in implementation.[1]

[1] The description of the SG index is as follows: "The SG Multi Alternatives Risk Premia Index represents risk premia managers who employ investment programs diversified across multiple asset classes while utilizing multiple risk premia factors. These managers trade multiple asset classes such as equities, fixed income, currencies, and in many cases commodities, and aim to capture a diversity of discrete risk premia, including most prevalently value, carry, and momentum." The index description of the Eurekahedge index is: "The Eurekahedge Multi-Factor Risk Premia Index is based on a weighted sum of bank-provided risk premia strategy swaps. The index is composed of multiple risk premia strategies managed by large global banks, and is designed to provide a broad measure of the performance of a diversified portfolio of systematic drivers of risk and return across various asset classes". See https://cib.societegenerale.com/fileadmin/indices_feeds/SG_MARP_Index_Monthly_Report.pdf and http://www.eurekahedge.com/Indices/Multi-Factor-Risk-Premia-Index-Methodology , respectively.

Exhibit 1: Performance Comparison of Two Risk Premia Indices



	Annualized Return	Annualized Stan Deviation	Sharpe Ratio	Cumulative Return	Correlation
SG Multi Alternatives Risk Premia Index	1.93%	3.64%	0.53	5.91%	0.53
Eurekahedge Multi-Factor Risk Premia Index	-2.16%	3.91%	-0.55	-6.33%	

Sources: Société Generale and Eurekahedge.

Kuenzi [2018] argues that risk premia strategies are ever changing, as managers respond to the aging and commoditization of some of the more popular risk premia strategies by exploring and implementing others. This would suggest that there is no current and precise definition of risk premia, especially with regard to which automated trading strategies are risk premia strategies and which are not. As markets shift and change, and as new entrants into various strategies impact the inherent profitability of those strategies, managers are inclined to adapt—to find new strategies, new approaches, and differentiated implementations of existing strategies, and to perhaps also add risk premia that are less well-known.[2] This dynamic is apt to lead to a continually evolving landscape with respect to the approaches taken to ARP strategies and portfolios, and thus to continued differentiation across these strategies and portfolios.

In the next section, we describe eight dimensions along which implementation is likely to differ. In the following section, we perform some simulation analysis in order to show how, even among a very narrow group of known strategies, portfolio returns can differ quite dramatically based on very simple differences in strategy and portfolio construction implementation. Finally, we conclude, with our final observations highlighting the heterogeneity of the risk premia marketplace. Our goal is to build on the observations of others by providing a more thorough taxonomy of the drivers of this heterogeneity and by making these ideas more concrete through simulation analysis.

Sources of Alternative Risk Premia Implementation Dispersion

The sources of dispersion among risk premia solutions can be quite varied. In this section we describe each of the eight drivers of dispersion that we have qualitatively identified, providing examples and / or further intuitions around how these dimensions of implementation dispersion behave. These eight sources of dispersion are then summarized in Exhibit 3.

[2] This is consistent with Lo's [2012] Adaptive Markets Hypothesis, which suggests [p. 24] that "behavior responds to changing market conditions," and that market participants "are intelligent, forward-looking, competitive investors who adapt to new economic realities."

Firm History and Philosophy, Strategy Construction Approach, and Strategy Inclusion

Firm history and philosophy (what Suhonen, et al. [2019, p. 26] refer to as "institutional DNA"), and which effectively drive a firm's core competencies, is likely one of the primary drivers. A firm with a history as an equity market neutral manager will approach risk premia somewhat differently than a firm with a history and culture as a trend following futures trader, which will be yet again different from a firm that has historically focused on volatility arbitrage or fixed income. The equity market neutral manager will likely have a portfolio overweighted to equity cross-sectional strategies such as value, momentum, low vol, quality, and perhaps even to other lesser-known cross-sectional equity strategies—and potentially with U.S., international developed, and emerging markets representations of these. The firm with a history as a trend follower may focus more on trend, mean reversion, and carry-related strategies. These cultural differences may also inform differences in the approach to representing the same risk premia strategy more broadly. As such, strategy inclusion, which likely grows out of a firm's investment philosophy and core competencies, is likely a key driver of differences. These firm history and philosophy dynamics likely form the basis of many of the differences among risk premia managers and are likely to be one of the primary drivers of the low correlation among them.

Amount and Source of Systematic Risk Exposures

Differences in systematic risk is another key driver of differences. Given that most of these strategies are designed to be market neutral, even small changes in systematic risk can lead to great dispersion among both risk premia portfolios as well as among nominally identical strategies. A portfolio with an equity beta of 0.25, for example, will have tracking error against an otherwise identical portfolio with an equity beta of zero. This also speaks to strategy construction from a hedging point of view. Different managers may take different approaches to making their strategies "neutral." This seemingly small decision, however, can drive substantial differences between the two strategies.

As a simple example, we look at two highly naïve small-minus-large strategies. We use a long Russell 2000 / short S&P 500 strategy. For the first version of the strategy, we take a 100% long position in the Russell 2000 futures and a short position of size β in the S&P 500 futures, where we obtain β by estimating a rolling 63-day regression of the returns of the S&P 500 futures against the returns of the Russell 2000 futures. We call this the fully hedged version. The partially hedged version is identical to the fully-hedged version, except that we sell only (β – 0.25) of the S&P 500 futures. [3] We perform this exercise for the 10-year period ending at 12/31/2018. The correlation between the two strategies is 0.91, which again is based only on a small difference in systematic risk in otherwise simplistic and identical strategies.

Unlike strategies that entail a large amount of systematic risk (e.g., long-only U.S. equities), risk premia strategies generally have little systematic risk, which serves to accentuate this effect. This issue therefore dovetails with firm history as a driver of differences. A manager emphasizing the volatility risk premia (especially if this emphasis is dependent on the implied volatility premium, which involve trading strategies that often exhibit some systematic risk) or a manager emphasizing directional strategies such as trend following (long equities for much of

[3] While we recognize that this strategy is unlikely to be implemented with a long exposure bias, our point is simply to provide an example of how such an exposure, when it does occur, can impact the correlation between two otherwise identical strategies.

the last 10 years) may see large tracking error against managers that do not emphasize these strategies.[4]

To illustrate the importance of neutrality to correlations, we consider both the Equity Market Neutral and the Long Short Equities categories in the hedge fund space. Specifically, we group all equity market neutral mangers in the Lipper / TASS, Morningstar, and eVestment universes and do the same for all long short equities managers. We then calculate the beta of each of these hedge fund categories (equally weighting the managers in each category to create an index) to the S&P 500 using 10 years of monthly data through December 2018. Our thesis is that if one of these categories has a lower beta to equities, it should also show a lower average pairwise correlation across managers. Exhibit 2 shows the results, which supports the notion that strategies that are run more neutral to systematic exposures tend to have a lower correlation with one another. Systematic risk is an important driver of correlation.

Exhibit 2: Beta and Pairwise Correlations of Equity Market Neutral Managers and Long Short Equities Managers

	Beta of an Equally-Weighted Group of Managers in this Category to the S&P 500	Average Pairwise Correlation of the Managers within Each Hedge Fund Category
Equity Market Neutral	0.09	0.07
Long Short Equities	0.48	0.28

Based on 10 years of monthly data ending December 2018. Sources: Lipper / Tass, Morningstar, eVestment, and Bloomberg.

[4] Dumontier [2018] makes a similar observation when analyzing risk premia performance during 2017. In general, the author finds that return dispersion that year was driven by differing levels of market exposure, differing strategy construction choices, and "how exposures in multi-factor funds are balanced."

Instrument Choice and Inclusion

Two similar strategies can also produce very different returns based on the returns of just a handful on instruments. This difference in the instrument universe for a given strategy can lead to substantial differences in strategy positioning, particularly in the case of strategies using few instruments, and especially during extreme market events. If, for example, one FX value strategy happened to be substantially long the Swiss Franc in on January 15, 2015, and another happened to be substantially short on the same date, we could see huge dispersion in returns between the two strategies. To illustrate this, we consider two FX value strategies—one that includes the Swiss Franc and one that does not.[5] Due to the extreme movements in the Swiss Franc around its depegging from the Euro, the daily correlation of these otherwise identical strategies was only 0.42 between January 2, 2014 and January 2, 2016 (isolating the two-year period that includes the extreme event). (See the Appendix for strategy construction information.)

Model Parameter Choices

Differences in model parameterization is another key dimension driving lower correlations among these managers. This is likely to be particularly important with regard to trend following, momentum, and mean reversion strategies. As an example, we consider two simple bond trend following strategies—one using a 5-day / 126-day moving average cross-over signal and the other using a 5-day / 252-day moving average cross-over signal. The daily correlation between these models during the 10-year period ending at 12/31/2018 is 0.64, suggesting that parameterization does indeed have an impact.

[5] On January 15, 2015 the Swiss National Bank abandoned the peg of the Swiss Franc to the Euro, which led to a one-day move of 17.62% in the CHF|USD exchange rate (USD dropped 17.62% against the Swiss Franc).

Instrument Weighting Mechanisms

Instrument weighting mechanisms also make a difference. Two strategies that are otherwise identical may experience somewhat varying return patterns driven by simple differences in the mechanisms by which the short and long sides are allocated. In a simple G10 carry strategy (perhaps G9, using USD as the base currency), for example, one manager may decide to equally weight the three most positive carry currencies on the long side of the book and to do the same with the three lowest carry currencies on the short side. Another manager might, in turn, do the same with the *four* most positively and negatively carrying currencies. Yet another manager may decide to differentially weight all nine currencies by their level of carry—by a schematic that may look like [-1 -0.75 -0.5 -0.25 0 0.25 0.5 0.75 1]. [6] This can be a substantial driver of implementation dispersion, especially for strategies with a limited number of instruments.

Data Choices

Choices regarding which external data sets to use and how that data is cleaned can lead to variations as well. This issue is most likely to impact cross-sectional equities strategies. There are often slight differences among data vendors in the way they approach the standardization of fundamental and consensus data across companies. If a manager is using a profitability measure, for example, such a measure may differ by vendor and / or by the manager's chosen computation / adjustments. The choices, for example, between the use of historical earnings, forward

[6] Dumontier [2018] provides a good example with regard to equity cross-sectional strategies: "Stock-weighting approaches also offer a number of implementation choices. Once the stocks are selected, should equal weights be favoured over a capitalisation approach? Or should weights depend on the strength of the score? How many stocks should be bought and sold? Should you build the long portfolio using index futures, or by also shorting single stocks? Should you risk-adjust the short leg to the long leg? Based on which risk: volatility, beta? Should the allocation be country-neutral? Sector-neutral? Or should both inter- and intra-sector bets be considered?"

earnings, the exact computation / source of forward earnings, and adjustments that might be made, can make a difference. In other markets, the ways in which historical data is cleaned (how to represent the Euro before its 1999 launch, for example) can also have an impact.

Execution Timing and Processes

Execution timing and execution process can also lead to differences. Performance can differ quite dramatically depending on whether trades for a given strategy are executed at the open, throughout each trading day (using a volume-weighted average price algorithm, for example), at the close, weekly, or perhaps within a certain mid-day window. A given options strategy might, for example, experience very different returns depending on when delta-hedging occurs. One strategy may neutralize delta exposures at the close, while another may neutralize mid-day. This can lead to a lower correlation between two otherwise identical strategies.

Crowding in Employed Strategies

Finally, the extent to which a strategy has been commoditized might have an impact on correlations. Kuenzi [2018] argues that as ARP strategies are popularized, some of these strategies may inherit a certain amount of "run-for-the-exit" risk, as profit-seeking investors often seek to derisk simultaneously during difficult market environments. This can lead to increased beta to the global risk factor for some of these strategies. As such, managers emphasizing these strategies (FX carry, for example), may show a higher correlation with one another, while managers with little allocation to these more commoditized strategies may exhibit a lower correlation to other risk premia managers.

Exhibit 3 summarizes the potential dimensions of risk premia portfolio implementation dispersion detailed above. While there may be other drivers of the low observed pairwise correlations, or other aspects related to those dimensions that we have identified, we believe that this taxonomy provides a solid foundation for understanding why the data appear as they do.

Exhibit 3: Primary Dimensions of Implementation Dispersion

#	Area of Implementation	Impact of ARP Manager Dispersion
1	Firm History and Philosophy, Strategy Construction Approach, and Strategy Inclusion	Firms with histories and core competencies in different asset classes and instrument types, and with different approaches to investing in general, will undoubtedly approach the risk premia exercise differently and will likely form very different overall portfolios based on both the nature of the strategies and which strategies they choose to include.
2	Amount and Source of Any Systematic Risk	Because most ARP strategies are run in a market neutral fashion, small differences in systematic risks can induce large amounts of tracking error between two otherwise identical strategies.
3	Instrument Choice and Inclusion	The choice of which instruments to include within a strategy's investment universe can drive differences, as one manager may experience extreme moves from a significant event in a given instrument while another does not.
4	Model Parameterization Choices	Many of these models involve various parameters regarding how much data to use, how to measure risk, signal smoothing, and a host of other elements that influence the strategy.
5	Instrument Weighting Mechanisms	Managers take varying approaches to the "portfolio construction" elements of strategy construction with regard to how the various long and short positions within a strategy are weighted, which can drive notable differences.
6	Data Choices	Different managers often use similar but different data sets in order to build similar models. They may also clean the data somewhat differently. This can then drive differences in strategy performance.
7	Execution Timing and Processes	While some managers may execute VWAP (volume weighted average price) throughout the day, others may trade at the open or at the close, or mid-day. Some also may be better at execution than others.
8	Crowding in Strategies Employed	A concentration in the more known strategies will also likely lead to a slightly higher correlation, as the preponderance of capital committed to the strategy is likely to lead to more correlation to systematic risk factors.

Simulation Analysis of Some Well-Known Risk Premia Strategies

In order to demonstrate our point, we perform simulations on a variety of simplistic and well-known risk premia strategies. We use strategies from what we call the "traditional grid," which is a group of 16 strategies formed using the futures and FX forwards markets within four asset classes (bonds, commodities, equities, and FX) and then applying four traditional approaches to risk premia (carry, momentum, trend, and value) to these asset classes. (See the appendix for strategy definitions and the instruments used in each.) Specifically, we create naïve implementations of 14 of these 16 potential strategies,[7] and then create variations of these based on 1) different instrument choice and inclusion, and 2) different instrument weighting mechanisms. These correspond to items 3 and 5 as shown in Exhibit 3. In other words, we are perturbing only two of the eight identified potential drivers of return dispersion. Later in this section, we create risk premia portfolios and vary the strategies that are included in these simulated portfolios (corresponding to item 1 in Exhibit 3).

Instrument Weighting

In terms of the instrument weighting mechanisms, we consider two sets of two choices: 1) signal-based differential weighting versus equal weighting, and 2) equal volatility weighting of the long and short sides of the strategy versus equal notional weighting. For the first choice, we

[7] We include 14 of the 16 potential strategies in the risk premia category by asset class grid. Specifically, we exclude Bond Value and Commodity Value, as there is no readily apparent way to robustly identify "value" in these asset classes (except perhaps in a fashion that is already represented within the Bond Carry and Commodity Carry strategies). Strategy descriptions are available in the Appendix, Exhibit A1; the list of futures and FX forward contracts used in each of these strategies is shown in Appendix A, Exhibit A2.

create a version of the strategy that weights longs and shorts based on signal strength (as noted above) by using something like [-1 -0.75 -0.5 -0.25 0 0.25 0.5 0.75 1] for a nine instrument strategy. We then create another version in which we go long an equally-weighted basket of instruments with the 25% of the signals that are most positive and go short the 25% of the signals that are most negative. For each of these two approaches, we have a version that equally volatility weights the long and short sides, and another version that equally notionally weights the long and short sides of the strategy. This gives us four weighting approaches in total.

Instrument Inclusion

In terms of instrument inclusion, we begin with an instrument universe as shown in Appendix A, Exhibit A2. Then, for each asset class, we find the number of instruments that represents 25% of the total (for FX, for example, this would be two instruments). This is the number of instruments we will remove from the base case instrument set. We then find all combinations of this number of instruments for removal in the various versions of the strategy. For FX, again, this gives us 36 possible combinations of instruments to exclude. As such, for each instrument weighting mechanism as described in the previous paragraph, we employ 37 versions of a given FX strategy—one version using all instruments and 36 using various seven-instrument subsets of the original nine instruments. This will give us 4×37=148 versions of a given FX strategy. We use the same methodology on all strategies in order to create a group of versions for each.[8]

[8] For all simulations in the ensuing analysis, we use daily return data running from January 4, 1993 to December 31, 2018. Note that none of the simulated returns generated in this analysis include the impact of transactions costs. Given that our objective is to examine strategy dispersion resulting from perturbations to items 1, 3, and 5 in Exhibit 3, with a general focus on correlations, we believe that the use of raw returns is appropriate.

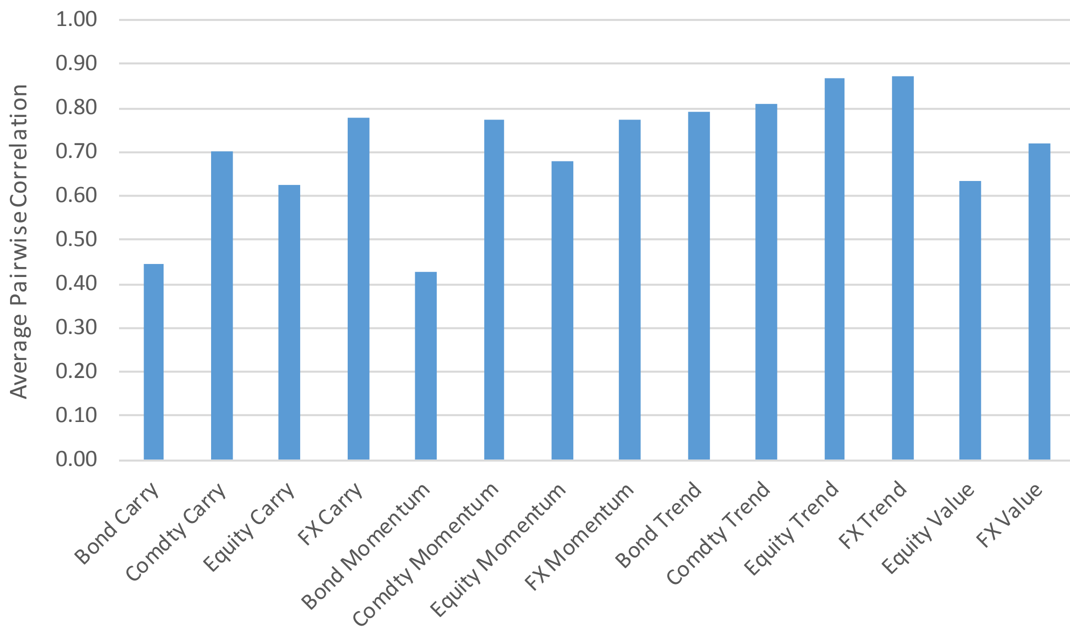
Given that the more instruments a strategy includes, the greater the number of potential combinations, we end up with 64 versions for each bond strategy, 4008 versions for each commodity strategy (driven by a larger number of possible instrument removal combinations reflecting the larger instrument set), 664 versions for each equity strategy, and 148 versions for each FX strategy. This gives us a total of 15,464 versions of strategies.

Strategy-Level Simulations

Exhibit 4 shows the average pairwise correlations across all versions of a given strategy.[9] It is first important to note that none of these average pairwise correlations are greater than 0.9. So perturbing just two of the items in Exhibit 3 can have a substantial impact in reducing correlations. Some of the strategies can actually have a quite low average pairwise correlation. The various versions of Bond Carry and Bond Momentum, for example, have an average pairwise correlation of less than 0.5. This is likely driven primarily by the use of a very limited set of instruments; removing / substituting two instruments (and the choice of those two instruments) can have a very large impact on the strategy. The strategies with the highest pairwise correlations are FX Trend and Equity Trend. This makes sense as these strategies tend to be dominated by a single systematic factor (the U.S. dollar and global equity beta, respectively).

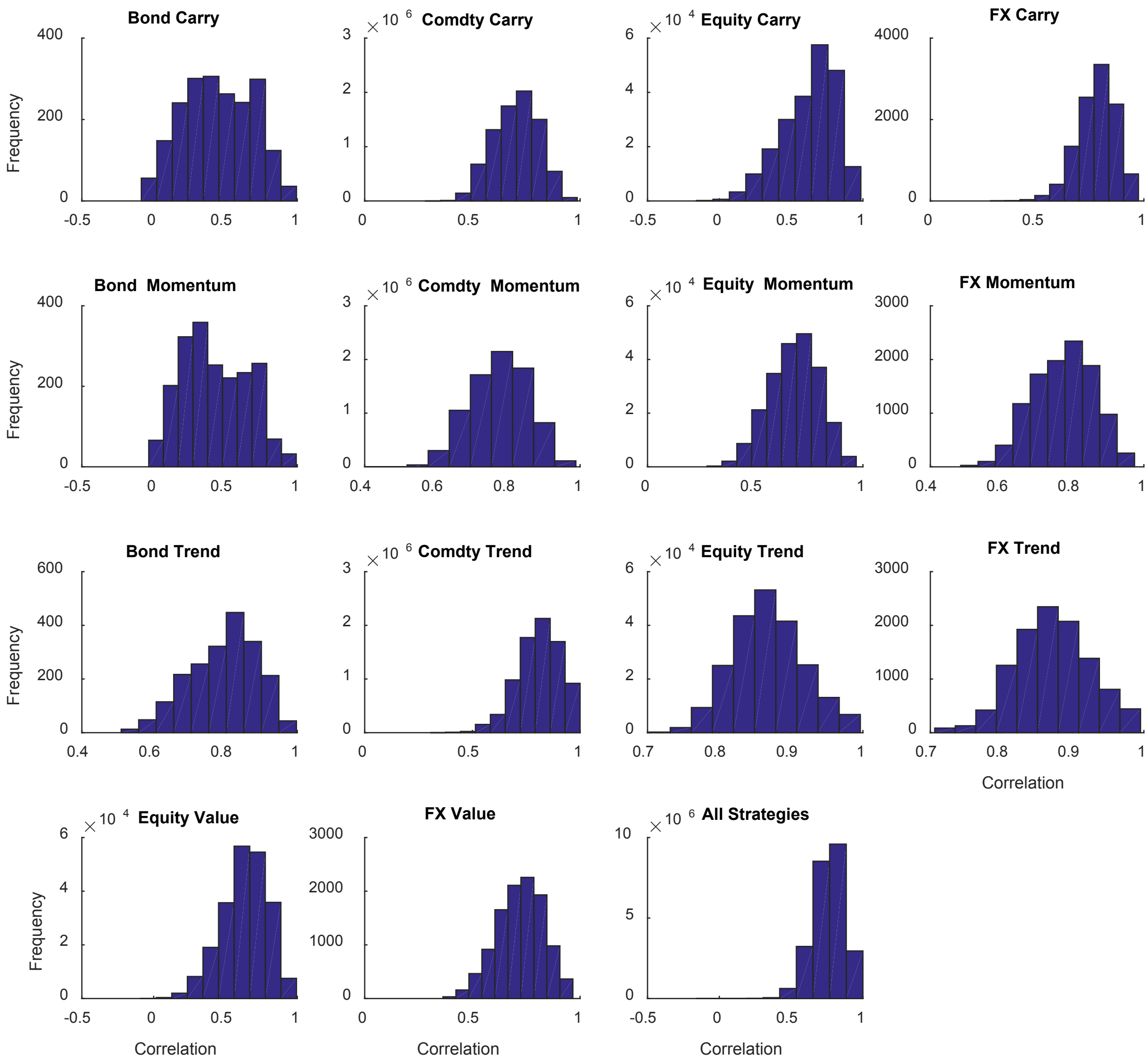
[9] The source for all raw data for the ensuing analysis is Bloomberg.

Exhibit 4: Average Pairwise Correlations of Various Versions of Each Strategy



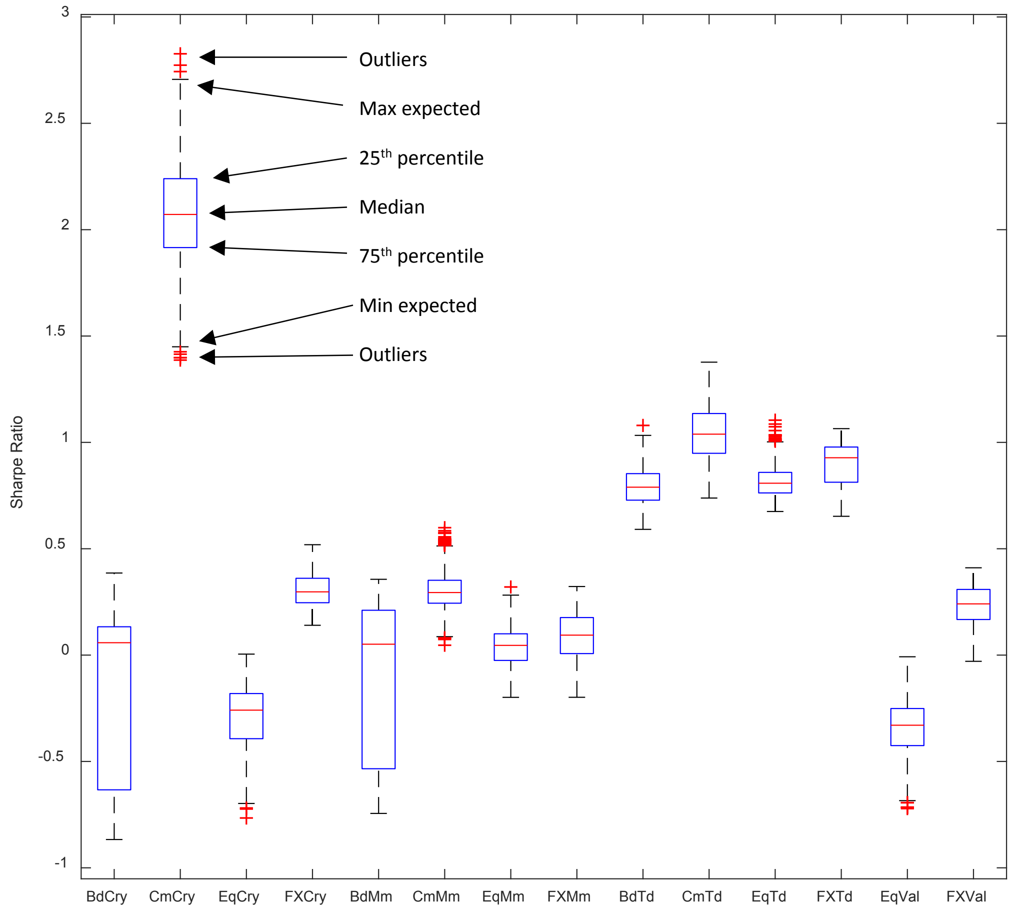
While the numbers in Exhibit 4 represent averages, Exhibit 5 provides us with some idea as to how extreme some of the versions of these strategies can be by presenting distributions of the pairwise correlations. Note that, although not visible to the naked eye, Bond Carry, Equity Carry, Bond Momentum, and Equity Value have versions that have a negative correlation with one another. It is also notable that 11 out of the 14 strategies have versions with correlations of less than 0.5 to one another. The final subplot brings together the data from the preceding subplots. It shows the distribution of the average pairwise correlations of all strategies, which finds its peak near the average of the average pairwise correlations across all strategy-level versions, which is a modest 0.76.

Exhibit 5: Distributions of Pairwise Correlations within Strategies



Finally, we consider the dispersion in Sharpe ratios across the various versions of the strategies in Exhibit 6. In this analysis, we are less concerned with the level of the Sharpe ratios than with their ranges. While many of the inter-quartile ranges are quite tight, the overall ranges are quite wide, with several showing a range of Sharpe ratios for the various versions of a strategy more than one unit wide. In other words, for some strategies, it wouldn't be unheard of to have a Sharpe of 1 or a Sharpe of 0 depending on how the strategy is implemented. It is also interesting to observe that several strategies have a substantial number of outliers.

Exhibit 6: Boxplots of Sharpe Ratios for the Various Versions of Each Strategy

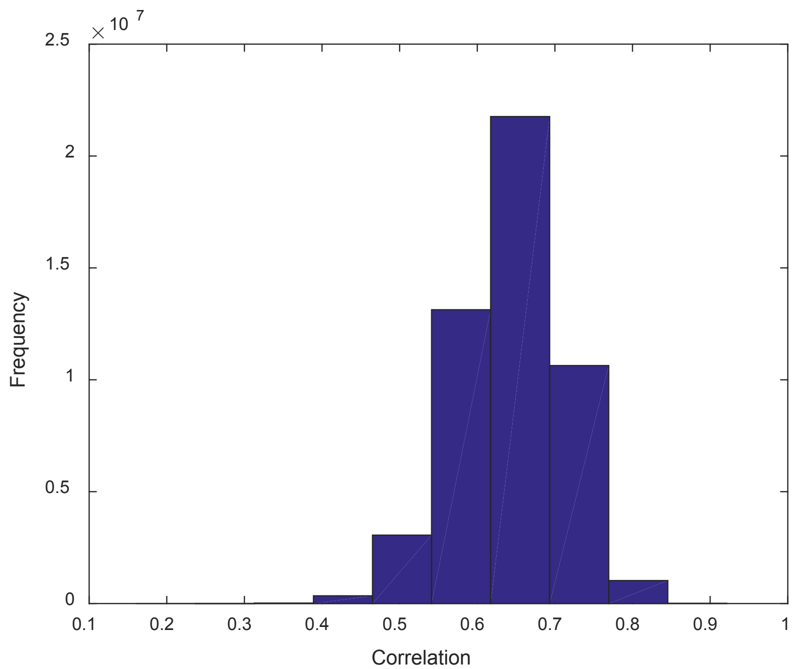


Portfolio-Level Simulations

We now extend the analysis to the portfolio level. Specifically, we simulate 10,000 portfolios that randomly choose 10 of the 14 strategies in our analysis. Then, within each of those 10 strategies, our simulation randomly chooses one version of that strategy. In effect, we have taken the two existing sources of dispersion we have already modeled and have now added to our analysis the dimension of strategy selection within a portfolio. We then perform analysis on this group of 10,000 simulated portfolio returns to see how different they are from one another.

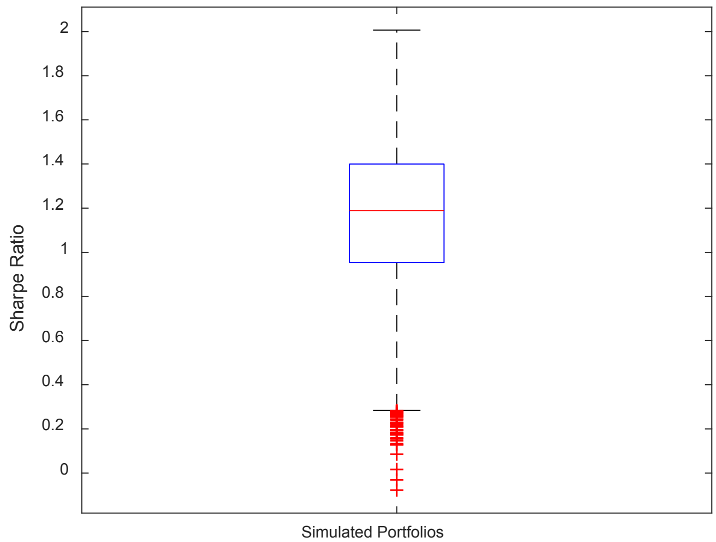
First, it is indeed interesting to note that these portfolios have an average pairwise correlation (taking the average of 49,995,000 correlations) of 0.64—not too far from the 0.53 correlation between the two risk premia indices shown in Exhibit 1. This is particularly interesting given that we are using a very limited set of strategies and are perturbing so few of the items described in Exhibit 3. Exhibit 7 shows the distribution of these pairwise correlations. While clustered around the average pairwise correlation, it is clear that the some of the pairwise correlations are quite low (the smallest simulated correlation is 0.16). This analysis helps to make concrete how it is that some risk premia funds can actually have a negative correlation with one another.

Exhibit 7: Distribution of Pairwise Correlations across Simulated Portfolios



Perhaps most interesting is the boxplot of the Sharpe ratios of the simulated portfolios in Exhibit 8. While the inter-quartile range is approximately between 0.95 and 1.5, the total range (including outliers) runs from approximately 0 to 2.

Exhibit 8: Boxplot of Sharpe Ratios for the Simulated Portfolios



In other words, differences in portfolio construction methodology, instrument choice, and strategy inclusion, even among this very narrow set of simplistic strategies, can result in portfolios that range from adding absolutely no value to those that are extraordinarily attractive.

Conclusion

Our objective in this article has been to provide a taxonomy of the sources of the observed return dispersion across different risk premia strategies and funds and to make the behavior of these sources of dispersion more concrete. As such, we first reviewed the observations of other authors regarding risk premia return dispersion in order to provide the broader context. We then identified, described, and provided some analysis around eight potential sources of this return dispersion. Finally, we performed simulation analysis at both the strategy level and at the portfolio level in order to render more concrete the substantial effect that some of these drivers of dispersion can have. In light of this analysis, it becomes more clear how easily returns can differ from provider to provider. Risk premia managers are investing in strategies, not in asset classes per se, and strategy construction and inclusion can vary quite significantly across these managers.

For investors, the foregoing analysis points to the importance of understanding first and foremost firm history, philosophy, and core competencies, as this can affect not only the related strategy inclusion decisions, but also many of the other items enumerated in Exhibit 3. It also suggests that familiarity with the strategies and a sense for the thoughtfulness and the quality of the micro-decisions that have gone into the strategy development process is of paramount concern.

In the absence of a high correlation across managers, comparing performance versus a benchmark is only one of many potential approaches to evaluating manager performance. Comparison against benchmarks should be supplemented with other metrics designed to evaluate the most important characteristics of these fund investments. A low correlation to traditional asset classes, for instance, is often cited as an attractive feature of these funds. As such, an ex-post evaluation of the fund's correlations to equities, bonds, currencies, and commodities may be important. If low directionality is cited as a desirable feature, then one might evaluate rolling correlations to traditional asset classes over time. Were the correlations to traditional asset classes time varying, or did they hover around zero fairly consistently? If an absolute return of Libor +300 is an objective, then how well did the manager accomplish that objective? A short list of key characteristics (along with benchmark relative returns) should be tracked ex-post and in comparison to competing managers as a way to build out a comprehensive picture of the quality of a given return stream.

Finally, a bottom-up understanding of the approaches of various managers is critical. Alternative risk premia strategy implementation matters, and there is no substitute for a more nuanced understanding of the potential offerings in the space.

Appendix A

We first provide a description of the strategies used. These are the same as in Kuenzi [2018].

Exhibit A1: List of Risk Premia Strategies

Strategy	Description
Bond Carry	Long the 10-year bond in countries with the steepest sovereign yield curves (2s10s spread) and short the countries with the flattest.
Commodity Carry	Long the most backwardated commodities and short the least backwardated commodities.
Equity Carry	Long the highest dividend yielding national equity markets and short the lowest dividend yielding national equity markets.
FX Carry	Long the currencies with the highest short interest rate and short the currencies with the lowest short rate.
Bond Momentum	Long the sovereign 10-year bond markets with the most postive returns in the eleven months preceding the most recent month, and short those with the lowest return over the same period.
Commodity Momentum	Long the commodities with the most postive returns in the eleven months preceding the most recent month, and short those with the lowest return over the same period.
Equity Momentum	Long the national equity markets with the most postive returns in the eleven months preceding the most recent month, and short those with the lowest return over the same period.
FX Momentum	Long the currencies with the most postive returns in the eleven months preceding the most recent month, and short those with the lowest return over the same period.
Bond Trend	Long a given sovereign 10-year bond market if the 5-day moving average of the contract price is above the 178-day moving average, and short if the 5-day moving average is below the 178-day moving average.
Commodity Trend	Long a given commodity if the 5-day moving average of the contract price is above the 178-day moving average, and short if the 5-day moving average is below the 178-day moving average.
Equity Trend	Long a given national equity market if the 5-day moving average of the contract price is above the 178-day moving average, and short if the 5-day moving average is below the 178-day moving average.
FX Trend	Long a given currency if the 5-day moving average of the contract price is above the 178-day moving average, and short if the 5-day moving average is below the 178-day moving average.
Equity Value	Long the national equity markets with the lowest price-to-book ratios and short those with the highest price-to-book ratios.
FX Value	Long the currency market that are selling below purchasing power parity, and short currency markets that are above purchasing power parity.

The instruments used within the 14 strategies are shown in the tables below.

Exhibit A2: Instruments Used in Risk Premia Strategies

Bonds

Australian 10-Year Bond Future
Canadian 10-Year Bond Future
Euro-Bund Bond Future
Long Gilt Future
Japanese 10-Year Bond Future
U.S. 10-Year Note Future

Commodities

Silver Future
Corn Future
WTI Crude Future
Live Cattle Future
Gasoline RBOB Future
Gold 100 Oz Future
NY Harbor USLD (Heating Oil) Future
LME PRI Aluminum Future
Brent Crude Future
LME Copper Future
Low Su Gasoil Future
Natural Gas Future
Soybean Future
Wheat Future

Equities

IBEX 35 Index Future
SPI 200 Index Future
S&P/TSX 60 Index Future
DAX Index Future
CAC40 Euro Index Future
FTSE 100 Index Future
FTSE/MIB Index Future
TOPIX Index Future
Amsterdam Index Future
OMXS30 Index Future
S&P 500 E-Mini Future

FX

Australian Dollar Forward
Canadian Dollar Forward
Euro Currency Forward
Brittish Pound Forward
Japanese Yen Forward
Swill Franc Forward
Swedish Krona Forward
New Zealand Dollar Forward
Norwegian Krone Forward

REFERENCES

Andersen, Mark, and Jason L. Ellement. "All About Outcomes: New Generation of Multi-Asset Class Strategies Focuses on Cutting Risk." Callan Institute. January 2018.

AON Hewitt. "Alternative Risk Premia, Alternative Price." August 2017.

Dumontier, Luc. "Bull Run Shows Up Differences in How Factor Strategies Are Built." Risk.net, January 31, 2018.

Kuenzi, David E. "Dynamic Strategy Migration and the Aging of Risk Premia." Working Paper, 2018.

Lo, Andrew. "Adaptive Markets and the New World Order." *Financial Analysts Journal*, Vol. 68, No. 2, March / April (2012), pp. 18-29.

Regan, David. "Overview of Multi-Asset, Multi-Risk Premia Investment Program Universe." Société Général, September 2017.

Skeggs, James, and Lianyan Liu. "Understanding Multi Alternative Risk Premia Strategies." Société Général, January 2019.

Suhonen, Antti, Jeremy Bryant, Shan Gao, and Andrew Cheung. "The MJ Hudson Allenbridge Alternative Risk Premia Fund Review 2019." MJ Hudson Allenbridge. February 2019.