Riskcasting ®

— Methodology Document[1] —

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Introduction

New and emerging technologies are creating ever more sophisticated approaches to this innovative area of asset allocation. Bramham Gardens articulates here the research it has developed and then shared in particular with S&P DJI in order to build a family of indices.

One key growth area in the financial industry has been the use of Artificial Intelligence (AI) to systematically assess current market conditions and position assets accordingly. In this paper, we discuss how the Riskcasting technology, developed by Bramham Gardens, evaluates current market conditions through investor views as expressed by options prices for the S&P 500. It should be noted that this approach can and is generalized to other equity markets in different geographies.

The approach uses a signal, derived from these data points to position an asset allocation to reflect market conditions.

[1] A Methodology protected by Patent FR2001209 @INPI in France on 02-07-2020

Influence of Investor Risk Attitude on the S&P 500

Many financial products have been developed around the S&P 500, including liquid derivatives such as options and futures. The liquidity of these derivative instruments provide insight into investor perspectives on market conditions.

It has been widely acknowledged that investors looking to hedge themselves at different strike prices and maturities tend to do so when reaching varying levels of volatility. Investors choose different instruments because they have specific market views, different investment objectives, and unique degrees of risk tolerance. The variation among these traits is synthesized using the notion of a "volatility surface," which captures the volatility for each strike price and maturity and fills in the gaps using interpolation techniques.

The volatility surfaces are built on a daily basis, using the relevant option-related information from each day. The changes in the shape of this surface reveal insights about the market's perspective on investment outcomes over differing time periods.

Once a volatility surface is created, the first step is to compare the levels of return retrieved from the corresponding implied volatilities with the range of returns observed for the index itself over similar periods of time. From there, a risk-averse investor can extract a quantity akin to the extra remuneration required for holding some risk. The derived ratio is called the discount factor and expresses the price of the uncertainty of time, given the risk held. An extensive surface of these discount factors can be inferred, because different strike prices and maturities correspond to different risks.

The second step is to derive a surface of risk aversion levels, also known as relative risk aversion.[2] This is accomplished using a closed-form deterministic methodology.[3] This analysis focuses on measuring the changes in the discount factor per level of strike, which leads to the transformation of the discount factor surface into a risk aversion surface. A level of risk aversion can be associated, on a daily basis, with each strike and time horizon. The consequences of these results are twofold. First, a daily measurement of investors' dynamic risk attitudes can be retrieved from put and call options on the index. Second, the investor's risk preferences can be clearly distinguished in relation to their time horizons and idiosyncratic market assumptions.

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[2] Relative risk aversion: In our application, the Arrow-Pratt measure of relative risk aversion or coefficient of relative risk aversion signals the current level of comfort or discomfort of an investor considering purchasing a stock with a forward-looking maturity, when it reaches a given predefined price. The discount factor is closely related to this measure of risk aversion in the sense that it provides a measure of the downward tilt on the future price expectation the investor applies, given her view on future uncertainties or risks.

[3] The closed-form deterministic methodology: In mathematics, a closed-form expression is a mathematical expression that can be described by a formula yielding a precise solution, as opposed to a result which can only be approximated using numerous empirical simulations.

Multiple time series of relative risk aversions per specific horizon and expected forward-market-price trigger (e.g., moneyness) are then derived. The next steps reduce noise in these time series and prioritize the time series that have the most impact.

Producing a Signal to Encapsulate Market Conditions

In order to filter the time series properly, this approach relies on two state-of-the-art techniques.

1) Signal Processing:[4] This process extracts the long-lasting risk aversion trends from each of the risk aversion time series using a technique called wavelet[5] filtering, which removes the inherent high frequency noise.

   Because each daily risk aversion surface is continuous, it is possible to extract a large quantity of time series from the succession of risk aversion surfaces. The focus is on the highest liquidity option maturities: 30, 60, and 90 days. In order to reduce dimensionality and consider only a few meaningful indicators, the filtered time series are aggregated by distinct moments in different maturities. This minimizes the redundancy of the information conveyed to mean, volatility, skew, kurtosis, and drift over the three maturities. These 15 non-overlapping output time series characterize the mood of the market in relation to future investments in the index.

2) Artificial Intelligence: In the next stage, a supervised machine-learning Bayesian classifier[6], which adapts to the data observed on a daily basis, is used to treat the output time series as high signal-to-noise input factors. These input factors

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[4] Signal processing: An electrical engineering subfield that focuses on analyzing, filtering, modifying, and synthesizing signals and time series such as sound, images, and biological measurements.

[5] A wavelet: A wave-like oscillation. Generally, wavelets are crafted to have specific properties that make them useful for signal processing. As a mathematical tool, wavelets can be used to extract information from many different kinds of data, including—but not limited to—audio signals and images. Sets of wavelets are generally needed to analyze data fully, as they account for different frequencies. It can be practical to use wavelets to denoise a signal and remove the high frequency noise, keeping only the significant trend elements. The Naïve Bayes Classifier: A family of supervised "probabilistic classifiers" based on applying Bayes' theorem with strong (naïve) independence assumptions between the features. This theorem is used to infer the likelihood of future market states given our understanding of the current histogram of relative risk aversions.

[6] The Naïve Bayes Classifier: A family of supervised "probabilistic classifiers" based on applying Bayes' theorem with strong (naïve) independence assumptions between the features. This theorem is used to infer the likelihood of future market states given our understanding of the current histogram of relative risk aversions.

subsequently determine whether current market conditions resemble those that preceded a significant rise or decline in the S&P 500.

The signal is ultimately derived by aggregating the three intermediary results of the AI algorithms, or model outcomes. The targets of the three model outcomes are:

1. The S&P 500 increasing by 1% over a day
2. The S&P 500 declining by more than 1% in a day
3. The absolute value of the S&P 500 changing by more than 1% a day

The combination of the three model-derived signals provides the Riskcasting Score, which determines the allocation. Although the target allocation is evaluated daily, the Score adjusts its allocation to equities and fixed income only when it moves from one cluster to another.

Looking at the results applied to the S&P 500 Riskcasting index

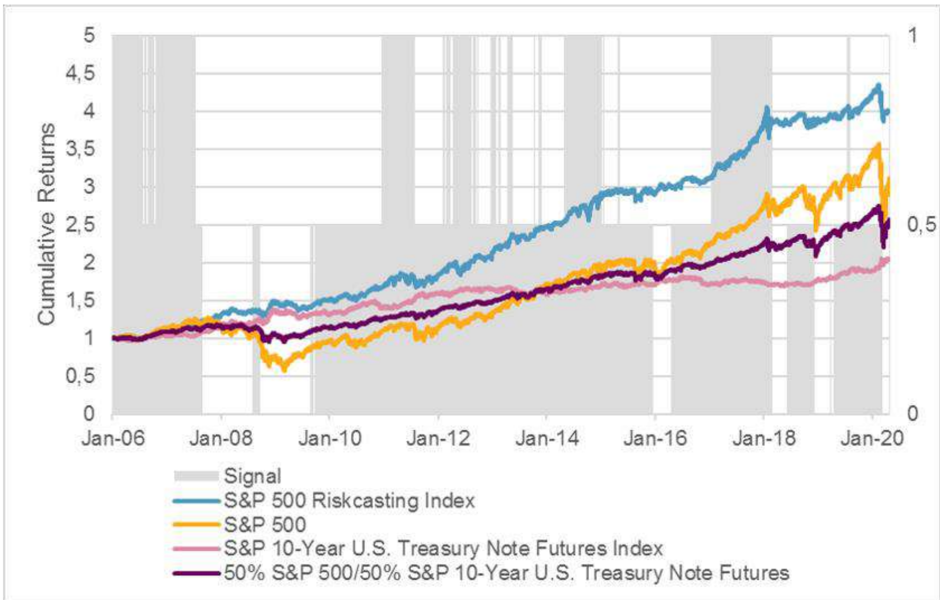

Exhibit 1: Cumulative Returns of the S&P 500 Riskcasting Index versus its Underlying

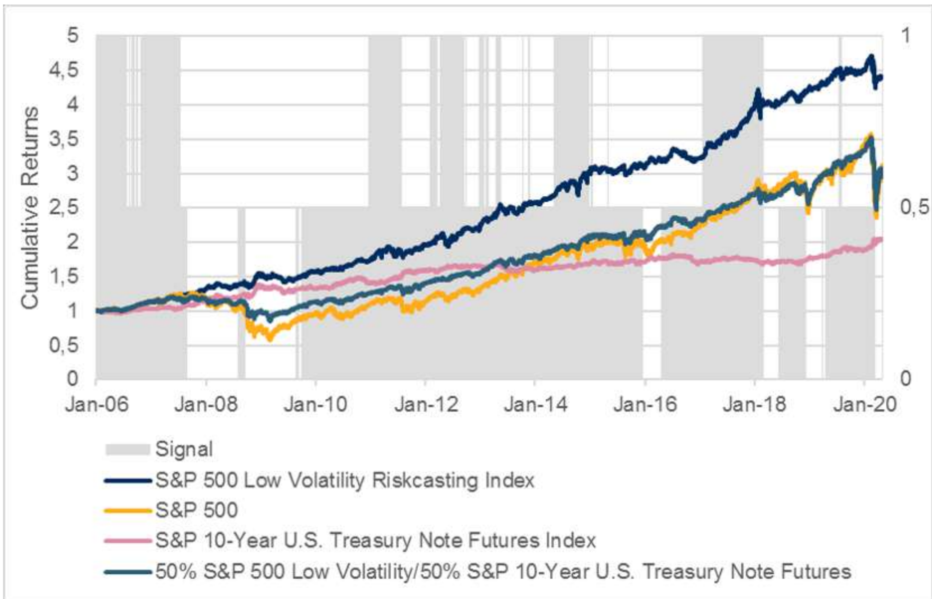

Exhibit 2: Cumulative Returns of the S&P 500 Low Volatility Riskcasting Index versus its Underlying

Exhibits 1 and 2 show the cumulative returns of the S&P 500 Riskcasting Index and the S&P 500 Low Volatility Riskcasting index against their underlying indices. Over the period studied, the signal was 29.8% bullish, 21.9% bearish and 48.2% neutral. Each signal switch triggered the index allocation to switch accordingly and as a result, both Riskcasting indices are shown to outperform their underlying. This is especially evident in bear market periods such as 2008 to 2009 and more recently YTD 2020, when the market saw significant drops in performance. During these periods, the Riskcasting signal triggered the index to allocate 100% to fixed income, thereby mitigating losses. Afterwards, the signal first indicated a neutral position, allocating 50% to equity and 50% to fixed income, before changing to a bullish position and fully allocating to the equity index.

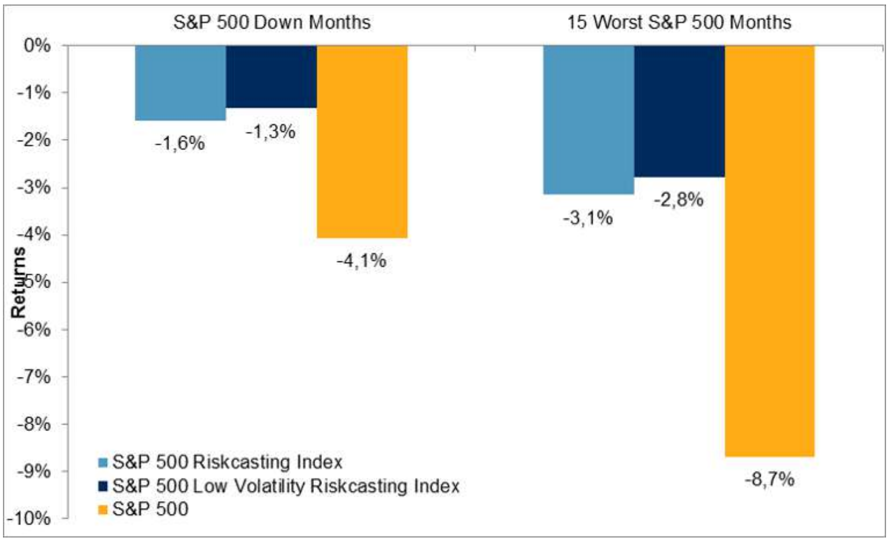

Exhibit 3: The Average Monthly Returns show that the Riskcasting Indices Offer Downside Protection

The downside protection offered by the Riskcasting Indices is evident in Exhibit 3. When the S&P 500 was down, its average monthly return was -4.1%, while the same metric for the S&P 500 Riskcasting and S&P 500 Low Volatility Riskcasting indices were -1.6% and -1.3%, respectively. Moreover, the average monthly return during the 15 worst months of the S&P 500 was -8.7%, whereas the returns for the S&P 500 Riskcasting (-3.1%) and S&P 500 Low Volatility Riskcasting (-2.8%) during those months were approximately 5% higher.

Exhibit 4: Risk/Return Characteristics

	S&P 500 Riskcasting Index	S&P 500 Low Volatility Riskcasting Index	S&P 500
ANNUALIZED RETURN (%)			
1-Year	0.84	0.95	0.86
3-Year	6.49	8.45	9.04
5-Year	6.46	7.85	9.12
7-Year	8.34	8.73	11.22
10-Year	9.77	10.51	11.69
Cumulative	10.18	10.92	8.18
ANNUALIZED RISK (%)			
3-Year	6.76	6.09	16.79
5-Year	6.37	6.14	14.70
7-Year	6.26	6.09	13.37
10-Year	7.18	6.73	13.82
Cumulative	7.46	7.07	14.98
RISK-ADJUSTED RETURN			
3-Year	0.96	1.39	0.54
5-Year	1.01	1.28	0.62
7-Year	1.33	1.44	0.84
10-Year	1.36	1.56	0.85
Cumulative	1.37	1.54	0.55

Given the recent events in the market, the annualized returns of the Riskcasting indices are lower than those of the S&P 500 because the index has been in the neutral and bearish positions since the beginning of the year (Exhibit 4). However, this results in the indices having lower annualized risk, and they outperform the S&P 500 in the short and long term on a risk-adjusted basis.

Conclusion

The Riskcasting approach is an innovative approach to asset allocation that utilizes Artificial Intelligence. The Riskcasting signal, developed by Bramham Gardens, measures investors' risk aversion and summarizes it into a few discrete market sentiment states. This signal is then used to create asset allocation rules. The resulting strategies rebalance dynamically between equity and fixed income sub-components according to the Riskcasting signal. As a result, the approach is meant to offer downside protection and show higher risk-adjusted performance relative to the equity indices per geography.