CAIA Member Contribution

Alternative Beta Strategies in Commodities

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Ever since the publication of Professor Harry Markowitz's work in 1952, modern portfolio theory has been one of the cornerstones of asset allocation and portfolio construction. Until recently, the principal building blocks used to construct investment portfolios have always been individual assets or asset classes. However, recent crises have brought into sharp relief the lack of diversification of many investment portfolios, despite appearances to the contrary. In reality, the correlation between traditional asset classes has increased steadily over the past decade, surging to alarmingly elevated levels during the 2008-09 financial crisis. Indeed, seemingly unrelated assets moved in lockstep, and portfolios once thought to be diversified did not weather the storm. This has led to some investors exploring risk-factor-based asset allocation as a potential new framework for portfolio construction, and looking at alternative beta strategies in an effort to rectify the 'defects' of conventional market portfolios.

Alternative beta strategies can take many different forms, with a variety of objectives. They can simply aim at reducing risks (the "risk-based approach") or enhancing returns through exposure to systematic factors (the "factor-based" approach). These strategies have become part of equity investing, owing to the swath of strategy indices that have come to market. However, the popularity of these strategies stems from not only a desire for diversification, but also an awareness that systematic risk factors explain the majority of long-term portfolio returns. In fact, many investors no longer consider their opportunity set as consisting solely of single assets or individual asset classes, but as risk premium that can be harvested systematically. In addition, the growing demand for transparency and a continued push to understand the different sources of return mean that investors have increasingly shown a predilection for such strategies.

In response to investor interest in the subject, we explore both risk-based and factor-based alternative beta indices in commodities, with a particular focus on the latter. This is conducted using both empirical research and surveys of existing indices. We also assess

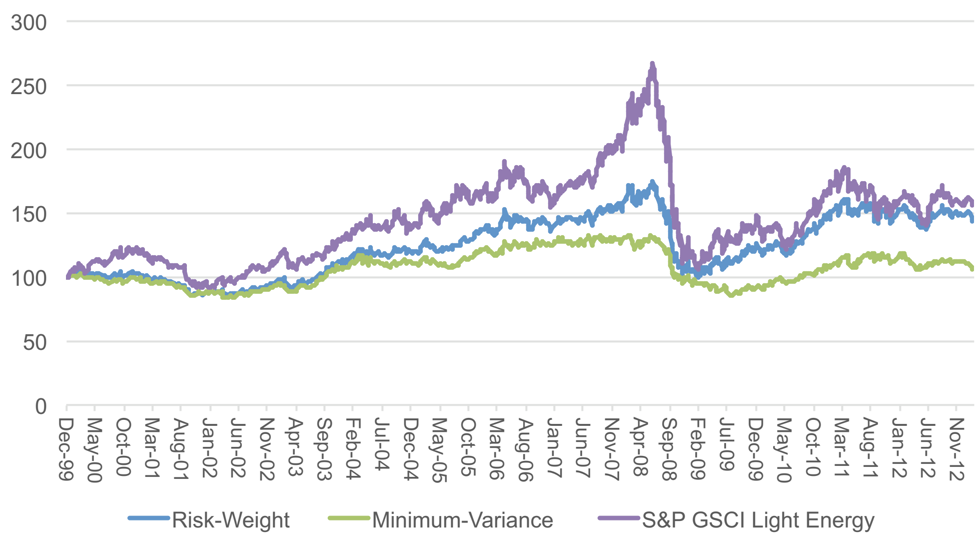

Exhibit 1a Performance of a Selection of Risk-Based Strategies

	Risk-Weight	*Minimum-Variance*	*S&P GSCI Light Energy*
Return	3.09%	0.85%	3.55%
Volatility	12.59%	10.56%	18.34%
Return per unit Risk	0.25	0.08	0.19
Maximum Drawdown	-43.4%	-36.6%	-60.7%

Exhibit 1b: Risk-Based Strategies - Historical Annualized and Return

Source: S&P Dow Jones Indices. Data from Dec. 31, 1999 to Dec. 31, 2012. Charts are provided for illustrative purposes. Past performance is not a guarantee of future results. Some data reflected in this chart may reflect hypothetical historical performance.

the merit of combining multiple systematic risk factors, either as part of a multi-asset portfolio or as a stand-alone commodity allocation.

1. Assessing Alternative Beta Strategies

1.1 Risk-Based Approach

Traditional indices, such as the S&P GSCI and the Dow-Jones UBS Commodity Index, primarily use global production and trading liquidity as primary determinants for assigning weights to sectors and commodities. In spite of having five distinct sectors, the S&P GSCI is heavily tilted towards energy, the sector that has seen the highest risk historically. Very often, its weighting reaches as high as 60-70%, equating to roughly 80-90% of the total risk in the index. In addition, of the 24 commodities composing the index, the smallest 10 components only have a token representation, collectively comprising less than 10% of the index.

On the other hand, the Dow-Jones UBS was designed with sector constraints that restrict the sector exposure to no more than a third of the index. However, energy is usually at this limit, and often makes up about 50% of the total risk exposure; this limit is often breached because of energy price rises in between annual rebalancings.

In light of the high-energy exposure in most major commodity indices and the recent upheaval in the financial markets, investors have become more conscious of the need to manage risks. As some market participants do not possess the capacity or information to forecast expected return accurately, a cautious passive approach may be to concentrate on reducing the risks of the commodity allocation. Here, we analyze two common approaches, represented in Figure 1a as the Risk-Weight portfolio and the Minimum-Variance portfolio. Essentially, the Risk-Weight index aims to allocate a similar risk budget to each of the five commodity sectors, whereas the Minimum-Variance index seeks to minimize the volatility of the index as a whole.

The results of the analysis in Figures 1a and 1b indicate that both risk-based strategies have succeeded in lowering risk. Given that the purpose of the Minimum-Variance strategy is specifically to minimize volatility, it is therefore, not astonishing that this index has achieved the lowest risk amongst all three indices. Equally unsurprising is that both risk-based strategies have yielded a lower annualized return than the S&P GSCI Light Energy benchmark, which is largely the result of having less exposure to energy,[1] one of the best-performing sectors during the examined period.

In addition, it is also apparent from the results that the Risk-Weight strategy was far superior to the Minimum-Variance when seen through the prism of risk and return trade-off. Indeed, commodity prices and volatility often go hand in hand with each other, particularly during periods of supply shortage, when both will spike upwards; this is why the distribution of commodity returns tends to be positively skewed. For this reason, merely targeting the lowest level of volatility appears counterintuitive, and a more satisfactory approach would be to target risk reduction by assigning a risk budget across different commodities and sectors.

1.2 Factor-Based Approach

A factor-based approach entails enhancing return by earning potential risk premium linked to systematic factors. In commodities, the most-well-known factors are value, curve, momentum, and liquidity, all of which are discussed in detail in the following sections.

1.2.1 Value Strategies

Value strategies generally seek to generate excess returns by selecting commodities whose prices are believed to be out of kilter with their supply-demand dynamics. At their most basic, they entail purchasing a portfolio of undervalued commodities, with the expectation that their prices will soar and eventually converge to a higher level. In combination with buying cheap commodities, additional return may also be harvested for investors able to sell overvalued commodities.

By implication, these strategies attempt to target commodities with the lowest inventories, which, due to the difficulty in replenishing supplies instantaneously, are expected to experience price appreciation. Generally speaking, shortages take time to be addressed through extra production, demand destruction, or both. How rapidly this adjustment occurs obviously depends on the commodity in question and the speed at which physical stocks can be replaced. Because of this, there is evidence of persistence in stock levels and physical stocks that should be seen as a 'cushion' to which commercial users can use in emergencies. Of course, if increases in supply outpace demand continually, inventories will eventually be depleted and they will no longer serve as a buffer. Therefore, an incentive must be offered to storage holders for reserves to be built up again, resulting in the term structure of the futures curve moving from backwardation to contango.

Many theories have been put forward to explicate the relationship between the term structure of the commodity futures markets and physical stock reserves, starting with Nicholas Kaldor's [1939] work in which he surmises that the differences between spot and futures prices (or the futures basis) can be ascribed to warehousing costs, interest foregone in storing a commodity and a convenience yield on inventory. A term coined by Kaldor, convenience yield, represents the benefit accrued to holders of physical inventories, rather than futures contracts, and reflects the market expectations about the future availability of a commodity.

In general, when a commodity is perceived to be scarce, the convenience yield strengthens as there is benefit from holding physical stocks, which minimizes the possibility of industrial stoppages caused by a dearth of relevant inputs to the production process.

An alternative theory revolves around the risk premium hypothesis popularized by Breeden [1980] and Jagannathan [1985] who view futures prices as encompassing a forecast of the future spot price and a risk premium. More recently, Gorton, Hayashi, and Rouwenhorst [2007] have attempted to link these two theories together. In their work, they have provided empirical evidence of the negative, non-linear relationship between convenience yield and the level of stocks, confirming that the inverse relationship becomes markedly more pronounced when there is a positive demand or negative supply shock. In addition to this, future spot prices will strengthen as there is more interest in hedging against future price risk, which in turn drives up the futures risk premium. The authors also argue that prior futures returns, spot price changes, and the futures basis carry pertinent information about the state of current inventories, and are thus correlated to futures risk premium. It is for this reason that the state of inventories can often be used to predict future

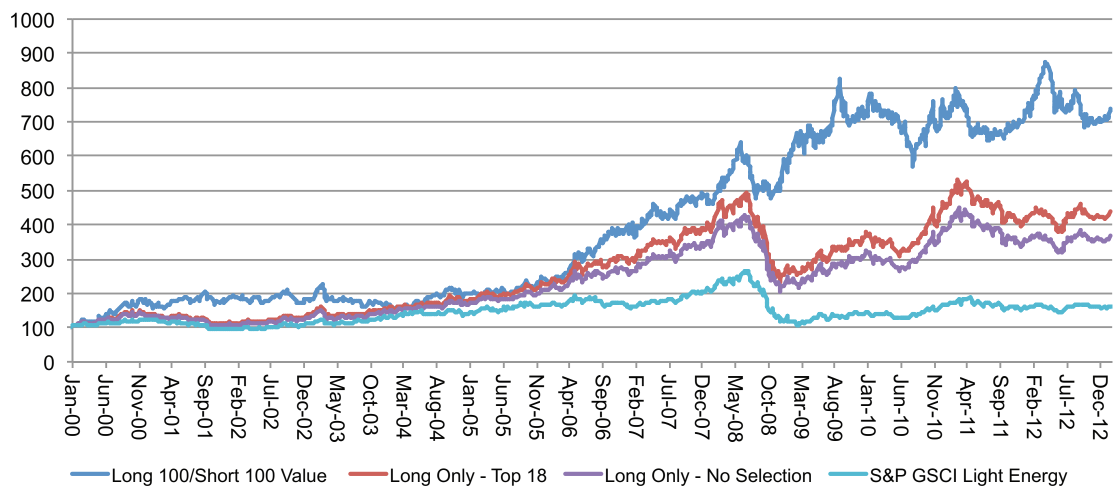

Exhibit 2a: Performance of a Selection of Value Strategies

	Long Only – No selection	*Long Only – Top 18*	*Long 100/Short 100 Value*	*S&P GSCI Light Energy*
Return	10.21%	11.68%	16.21%	3.62%
Volatility	17.93%	18.79%	20.40%	18.34%
Sharpe Ratio	0.43	0.49	0.67	0.06
Maximum Drawdown	-52.4%	-53.2%	-31.3%	-60.7%

Exhibit 2b: Value Strategies: Historical Annualized Risk and Return
Source: S&P Dow Jones Indices. Data from Dec. 31, 1999 to Dec. 31, 2012. Charts are provided for illustrative purposes.
Past performance is not a guarantee of future results. Some data reflected in this chart may reflect hypothetical historical performance.

excess return.

With stock levels being so fundamental in price formation, it is reasonable to question the wisdom of using a price-based proxy rather than the actual inventory levels. Aside from the onerousness associated with gathering the data, it is often impractical to do so, simply because they are published at different times of the year and are often plagued with inaccuracies and time lags. A case in point is when the U.S. Department of Agriculture had to commission a study on its estimate of U.S. corn stockpiles following widespread industry concerns about the accuracy of the Bellwether Quarterly Report (Stebbins, 2013). For lack of a better alternative, analyzing the futures basis remains the most effective and transparent gauge of the interaction between supply and demand.

Typically, when the market anticipates a supply shortage, the prices of the futures contracts across many (if not all) maturities increase, inducing an upward, parallel shift of the entire futures curve. This is usually accompanied by a steepening of the front end of the curve as short-term contracts will continue to be pricey, until such time as the shortage is eased. In the face of such uncertainty, investors may avail themselves of the opportunity to earn compensation for bearing the volatility of future spot prices.

A number of indexes have been launched in recent years to harvest this 'risk premium'. They involve equal-weighting a small number of commodities selected based on their perceived scarcity. Whilst they have overall delivered strong returns, their exposure tends to be fairly concentrated, owing to the small number of commodities included in the index. Furthermore, once the commodities are selected, they are given equivalent weights, regardless of their valuation in relation to others in the universe.

In view of this, we attempt to assess the efficacy of adopting a scheme that assigns different weights to commodities based on their respective valuation, and the necessity of active selection for these strategies to perform. To ensure the rigorousness of the study, we have not applied any individual commodity or sector exposure cap. The investigation starts by computing the front-year slope of all the commodities within the S&P GSCI Light Energy Index. They are then ranked from smallest to largest, with the smallest accorded the highest weighting because these are considered to be the cheapest. A number of iterations have been conducted to test whether a persistent effect exists, with the most relevant results displayed in Figures 2a and 2b.

For the long-only versions of the simulation, we simply weight each commodity in the S&P GSCI Light Energy Index by the gradient of its front-year futures slope. Next, we examine whether active selection improved the performance by targeting only the cheapest 18 commodities. Choosing 18 commodities is by no means fortuitous.[2] Rather, it is the result of striking a balance between having sufficient constituents in the indices and recognizing that commodities in the top quartiles, sorted by their average slope, have historically outperformed. Lastly, we appraise long-short strategies using a long 100/short 100 strategy, in which the cheapest 10 commodities are bought and the most expensive 10 commodities are sold simultaneously.

The analysis above shows that value strategies have performed well over the period under investigation, with all of them achieving a higher Sharpe ratio than their benchmark, the S&P GSCI Light Energy Index. It should be pointed out that a simple change in the weighting scheme applied to the same underlying universe as the benchmark already allows some benefits to be reaped, whilst keeping the overall risk at bay. Active selection through eliminating the most overvalued commodities also appears advantageous. This is not unexpected because the ability to sell short overvalued assets usually enhances the performance of relative value strategies. For this reason, the long 100/short 100 version has achieved the best return overall, but this enhanced return comes at the risk of assuming higher active risks. Another important observation from Figure 2b is that all three strategies have suffered lower maximum drawdowns than the benchmark.

Despite the attractiveness of value strategies, they can experience periods of underperformance too, especially in periods where commodity fundamentals play a secondary role in the general macroeconomic environment in influencing prices. This was the case in 2011 and 2012, when commodities—like most other risk assets—suffered as a result of the Eurozone crisis; both long-only value strategies underperformed the benchmark by about 2% per annum. It follows from this that such strategies are the most effective when the fundamentals of different commodities are divergent, enabling value to be extracted via active selection.

1.2.2 Curve Strategies

Broadly speaking, first-generation indices are long-only passive indices that roll their front-month futures position on a regular basis in order to maintain exposure to commodities. During periods of backwardation, positive carry can be earned through the simultaneous sale of a more expensive expiring contract and the purchase of a cheaper subsequent contract. Conversely, during periods of contango, investors suffer from negative carry, which erodes their overall return. Though not stated explicitly, these indices by construction assume that backwardation is the norm in commodity markets.

However, for some time since the onset of the financial maelstrom, the futures curves of many commodities have been in contango. This has inspired the development of a variety of curve strategies that attempt to mitigate the negative effect of this term structure by rolling into contracts with a longer maturity. By far the most popular means to generate excess returns over conventional benchmarks, these strategies aim to capture a risk premium for taking greater price uncertainty associated with futures contracts on the long end of the curve. According to the "Theory of Normal Backwardation" by Keynes (1930), this is the consequence of producers being willing to sell futures at a lower price than spot so as to transfer the price risk. In so doing, they exert enormous pressure on the supply side of the futures

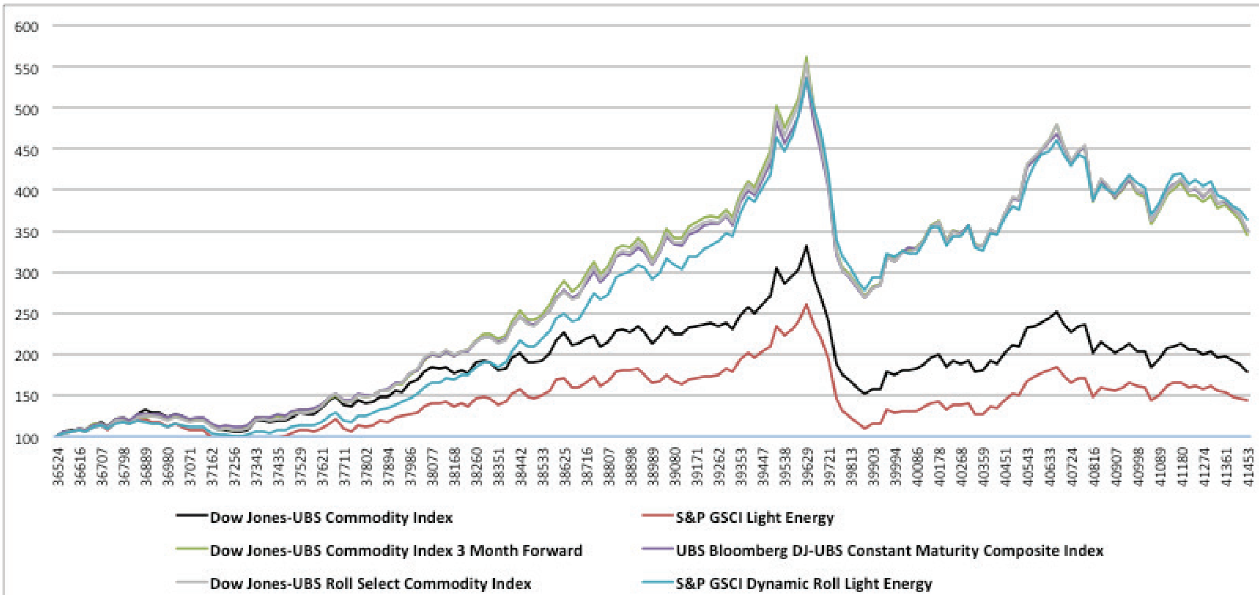

Exhibit 3a: Performance of a Selection of Curve Strategies

	Dow Jones-UBS Commodity Index	S&P GSCI Light Energy	Dow Jones-UBS Commodity Index 3 Month Forward	Dow Jones-UBS Roll Select Commodity Index	S&P GSCI Dynamic Roll Light Energy
Return	4.4%	2.7%	9.6%	9.7%	10.1%
Volatility	17.3%	17.5%	16.4%	16.5%	15.0%
Sharpe Ratio	0.11	0.01	0.43	0.44	0.51
Active Return (w.r.t. the Corresponding Base Index)	-	-	5.2%	5.4%	7.3%
Tracking Error	-	-	3.3%	3.0%	4.6%
Information Ratio	-	-	1.57	1.76	1.58

Exhibit 3b: Curve Strategies: Historical Annualized Risk and Return

Source: S&P Dow Jones Indices. Data from Dec. 31, 1999 to Dec. 31, 2012. Charts are provided for illustrative purposes. Past performance is not a guarantee of future results. Some data reflected in this chart may reflect hypothetical historical performance.

market, making them more vulnerable than consumers.

In theory, commodity producers sell long-dated contracts at a discount in order to hedge their output, whereas consumers often buy short-dated contracts at a premium in order to secure near-time consumption. It has been argued that such structural characteristics may allow investors to capture a systematic risk premium by purchasing long-dated contracts. However, although these assertions may hold true in theory, it is more complex in practice. In reality, different consumers and producers are likely to pursue an amalgam of hedging strategies, which must conform to their price expectations and the company's policy. Obviously, these strategies will invariably change depending on the commodity in question, and it would be a facile generalization to refer to producers and consumers as though they were always acting in concert in their respective groups.

A further complexity arises from the number of non-industrial participants in the futures market, such as index investors and hedge funds, and it would therefore be more accurate to suggest that the shape of the curve is determined by the overall impact emanating from the interaction of different market participants, all of whom have different goals and time horizon. For example, for most of 2011, the LME copper market traded in backwardation. This was due to the strength of Chinese demand[3] rather than significant hedging activity by miners—many of which elected not to hedge, as they were enjoying record prices for their metal.

The simplest implementation of curve strategies involves systematically rolling into forward contracts of a pre-defined maturity, such as the three-month contract. For instance, the Dow Jones-UBS Commodity Index 3-Month Forward and the S&P GSCI 3-Month Forward Index employ this strategy. Other static strategies, such as the S&P GSCI Enhanced Index, accord slightly more flexibility to the rolling process by utilizing a broader part of the forward curve whilst taking into consideration the specificities of different commodity markets in the choice of expiry contracts. Another way of implementing the curve strategy is to invest in contracts of different tenors. For instance, instead of opting for a single contract, the JPMorgan Commodity Curve Index holds contracts across different maturities in accordance with the open interest or liquidity of each tenor.

Even more dynamic strategies—such as the S&P GSCI Dynamic Roll and the Dow Jones-UBS Roll Select indices—have also garnered much interest in recent years. Unlike their static counterparts, the objective is not only to minimize the effect of contango, but to maximize the effect of backwardation by adopting a different roll strategy with respect to the term structure of the commodity concerned. In practice, they roll into futures contracts with the lowest implied roll cost when a commodity trades in contango, and roll into futures contracts with the highest implied roll benefit when a commodity trades in backwardation.

Over the long term, all four curve-strategies have delivered higher returns than their respective benchmarks, despite the many methods that can be used to implement such strategies (see Figures 3a and 3b). This may suggest that a sizable portion of the outperformance from these strategies derives from a systematic source of return. To investigate this, we attempt to attribute the return of these strategies to three

Index	*Regression Alpha*	*Market Factor*	*Systematic Curve Factor*	*R-Squared*
Dow Jones-UBS Roll Select Commodity Index	1.6%	0.99	0.69	0.99
P-Value	*(0.5%)*	*(0.0%)*	*(0.0%)*	
S&P GSCI Dynamic Roll Light Energy	2.3%	0.87	0.82	0.97
P-Value	*(0.6%)*	*(0.0%)*	*(0.0%)*	

Exhibit 3c: Performance Attribution of Curve Strategies
Source: S&P Dow Jones Indices. Data from Dec. 31, 1999 to Dec. 31, 2012. Charts are provided for illustrative purposes. Past performance is not a guarantee of future results. Some data reflected in this chart may reflect hypothetical historical performance.

sources of return; namely, market factor, systematic curve factor, and dynamic alpha factor (see Figure 3c).

In the analysis, the market factor is represented by its corresponding benchmark index whilst the curve factor is estimated as the difference between the monthly returns of the three-month forward index and its benchmark index. The last factor—dynamic alpha—is approximated by the regression alpha that cannot be explained either by the market factor or the systematic curve factor and thus may represent the additional return generated from the dynamic nature of the strategy. The results in Figure 3 show that both dynamic strategies have significant exposure to the systematic curve factor, with their coefficient of determination (R2) being very close to one. Both the dynamic alpha factor and the tracking error are higher for the S&P GSCI Dynamic Roll Light Energy Index than the Dow-Jones UBS Roll Select Index. This may indicate that the former index is more dynamic in nature and deviates more from the benchmark, allowing it to make a more substantial return (7.3% versus 5.4% per annum). All in all, both dynamic strategies have realized a high return, but whereas static strategies roll only forwards, dynamic strategies can roll both forwards and backwards, potentially giving them an edge over static strategies.

Notwithstanding the similarity of the return achieved by different curve strategies over the long run, they are likely to behave quite differently over the short run. In particular, curve strategies will underperform when the term structure of most commodities trades in backwardation and in this instance, it would be more desirable to be positioned at the front month of the curve in order to take full advantage of the positive carry. Both static and dynamic curve strategies should perform well in respect to their benchmarks in periods of contango, but the latter should reign supreme in periods where the term structure of different commodities is dissimilar, which lends itself to a more flexible rolling mechanism.

1.2.3 Momentum Strategies

Momentum strategies generally aim to exploit the persistence in commodity returns, which are believed to derive from psychological biases exhibited by investors and behaviors displayed by industrial market participants. This may explain why commodity returns tend to exhibit high degrees of positive autocorrelation (Kat and Oomen, 2006).

Psychological research has explored a variety of biases and irrationalities that are believed to affect investment decisions. These biases are fundamental parts of human nature and have been well-documented in the behavioral finance literature. They are not peculiar to commodities, applying equally to other asset classes. One such bias, known as the 'disposition effect', relates to the tendency for investors to sell appreciating assets too quickly and keeping depreciating assets for too long. This stems from the brain's tendency to make mental shortcuts rather than engage in longer analytical processing (Chen et al. 2007) and may partially explain why momentum return exists. Besides investor psychology, the behavior of industrial market participants may also bring about price trends. Taking Kansas wheat as an example, consumer demand remains fairly stable throughout the year whilst production can vary immensely, as planting usually begins in September of the previous year. If during harvest in June and July there is a sudden surge in demand, and this is not satisfied by imports, prices will inevitably go up, giving rise to positive price momentum. The behavior of industrial hedgers can equally cause prices to trend, such as when metal mining conglomerates execute large hedging programs. Momentum strategies can be implemented in a variety of ways and, depending on the method chosen, can have markedly different replication costs. In general, they take both long and short positions and consist of at least two steps; the first of which is to determine what position to take for each commodity; the second is to decide on an appropriate weighting scheme. An example of a simple momentum strategy is the Morningstar Long/Short Commodity Index, which uses a simple moving average signal to determine the trading position of each commodity, which is then weighted by the open interest of its futures. In comparison, the S&P Systematic Global Macro Commodities Index is more complex. It first establishes the trend of each commodity and employs statistical tests to verify the stability of that trend. It then gives equal risk capital allowance to each sector and then equal weight to the constituents within that sector. The resulting portfolio is then geared up to a target volatility level adopted by the average managed futures/CTA fund.

An important advantage of momentum strategies is that they may provide downside protection during sharp market corrections, whilst maintaining upside participation during bull markets. For instance, Figures 4a and 4b show that the S&P GSCI Light Energy Index lost more than 50% during the 2008-09 crash. In contrast, the S&P Systematic Global Macro Commodities Index and the Morningstar Long/Short Commodity Index were not only more resilient over the same period, but they managed to capture some upside during the 2010-11 price rebound.

Undoubtedly, these strategies also experience periods of subpar performance. In range-bound markets where there is no clear trend, they are unlikely to generate returns. For instance, in the oscillating markets over the last two years or so, momentum strategies—irrespective of their construction—posted disappointing results as compared with their benchmarks. This underscores the danger of relying on a single strategy to structure an investment portfolio.

1.2.4 Liquidity Strategies

Financial investors have long assumed the role of providing liquidity to other market participants in the futures market. In recent years, as they have become more accustomed to commodities as an asset class and grown in sophistication, much innovation has been witnessed in the development of indices fulfilling a wide variety of objectives. In spite of this, first-generation indices—especially the S&P GSCI and the Dow Jones-UBS Index—still take the lion's share of the assets under management (roughly USD 78 billion apiece) for passive investors seeking commodity exposure via passive funds or structured products.

An important characteristic of these first-generation indices is that they roll over a similar window. For instance, the S&P GSCI rolls over five days between the fifth and ninth business day, whereas the Dow Jones-UBS Index rolls between the sixth and tenth. As a result,

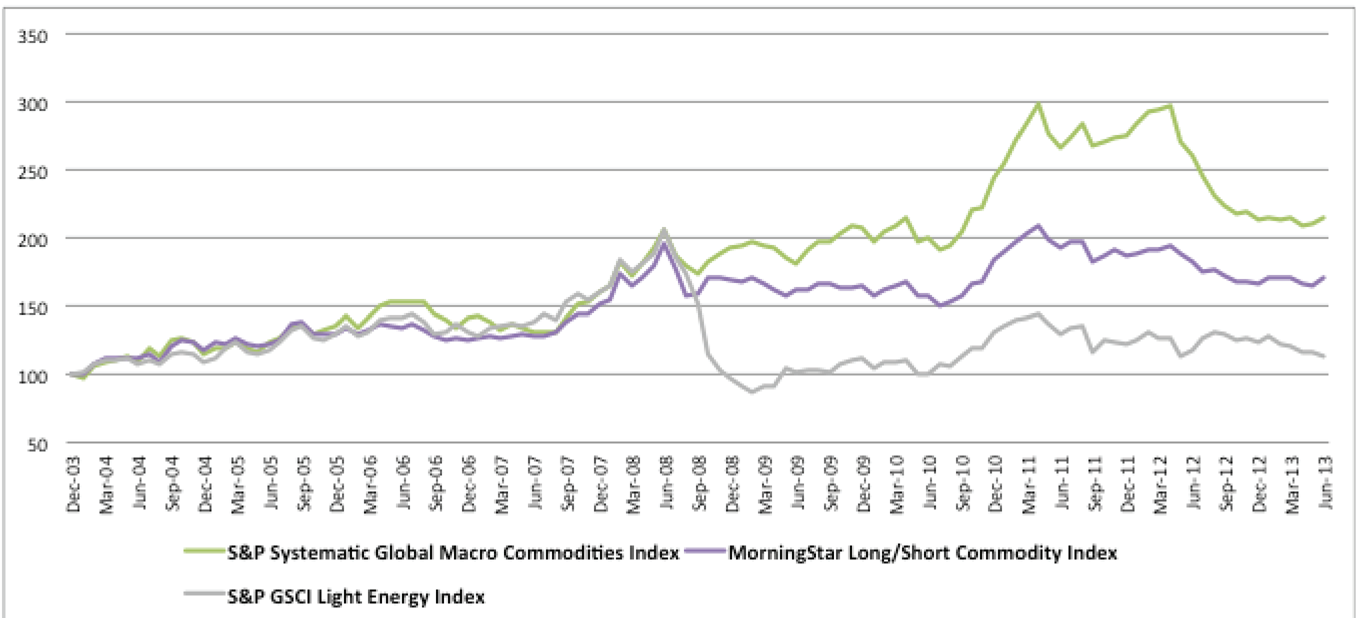

Exhibit 4a: Performance of a Selection of Momentum Strategies

	S&P GSCI Light Energy Index	MorningStar Long/Short Commodity Index	S&P Systematic Global Macro Commodities Index
Return	1.3%	5.8%	8.3%
Volatility	19.2%	13.1%	15.3%
Sharpe Ratio	-0.04	0.28	0.40

Exhibit 4b: Momentum Strategies - Historical Annualized Risk and Return
Source: S&P Dow Jones Indices. Data from Dec. 31, 1999 to Dec. 31, 2012. Charts are provided for illustrative purposes. Past performance is not a guarantee of future results. Some data reflected in this chart may reflect hypothetical historical performance.

sizable investment flows go into simultaneously selling the front-month and purchasing the following nearby-month contracts, and the rigidness with which the indices must perform the roll may give rise to a liquidity premium that can be harvested.

In view of this, we evaluate whether a persistent source of return is present if the roll takes place outside of the standard window, and also assess whether modifying the length of the roll period can also contribute to higher levels of return. The probe starts by adopting the same methodology as the S&P GSCI Light Energy Index, albeit with a variety of rolling schedules. In order to visualize clearly the return of the factor, a market-neutral portfolio is created by going long the newly created portfolios and short the standard S&P GSCI Light Energy Index. The results of this can be found in Figures 5a and b.

The analysis above shows that there may be value in adopting a different rolling schedule. Prior to 2007, adopting any of the five liquidity strategies would have yielded a reasonable return, though with slightly higher volatility. However, as more innovative indices came to market, this benefit seemed to have somewhat dissipated and the return from these strategies decreased. In 2010, the erstwhile outperformer—Strategy 1—started posting poor performance, and since 2008, outperformance came from strategies that commenced the roll from day nine and they delivered, on average, an alpha of between 0.4-0.5% per annum.

In light of the changing liquidity conditions, a possible improvement to the static approach explored above would be to adopt a dynamic rolling schedule in which the roll would occur over a rolling window that is determined on an ongoing basis, rather than defined in advance. This sounds reasonable as, based on Figures 5a and b, adopting different roll schedules can produce very different returns depending on the time period in question. Obviously, this would come at the expense of transparency. Finally, the analysis finds no evidence to

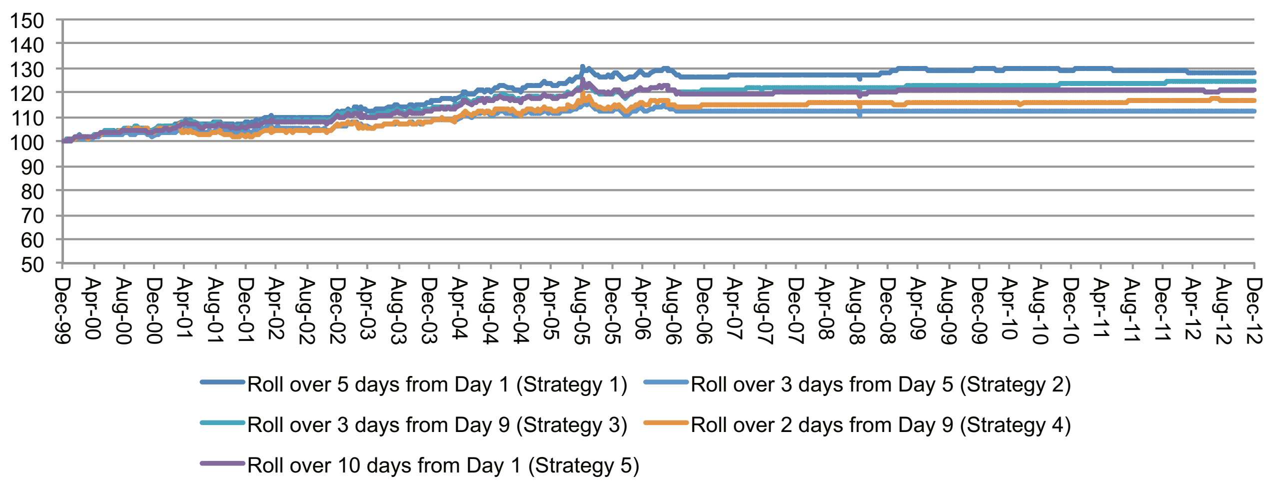

Exhibit 5a: Performance of a Selection of Momentum Strategies

	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5
Return	1.92%	0.89%	1.72%	1.22%	1.46%
Volatility	2.13%	2.15%	2.34%	2.46%	2.15%
Return per unit Risk	0.90	0.41	0.73	0.50	0.68

Exhibit 5b: Liquidity Factor Return: Historical Annualized Risk and Return
Source: S&P Dow Jones Indices. Data from Dec. 31, 1999 to Dec. 31, 2012. Charts are provided for illustrative purposes. Past performance is not a guarantee of future results. Some data reflected in this chart may reflect hypothetical historical performance.

show that lengthening or shortening the rolling window enhances or reduces return on a consistent basis.

Unquestionably, liquidity is by far the smallest source of return, compared to the other sources discussed in this paper, but it is nonetheless unique to the commodity markets.

2. Combining the Different Sources of Risk Premia

Factor-based strategies provide independent sources of risk premia in the commodity markets, and can serve as building blocks for combinations of different commodity strategies and asset allocations in multi-asset portfolios. In general, their periods of underperformance do not always coincide with each other (see Figure 6a). This may imply that they may offer the potential to diversify risk, as their return may be driven by mostly different risk factors.

From Figure 6b, it is also clear that the correlation between the strategies is low and that the correlation between these strategies and the broad index is low to negative, with the exception of the momentum factor. This is expected because commodities on an upward price trend automatically increase their representation in the broad index, but unlike the broad index, momentum

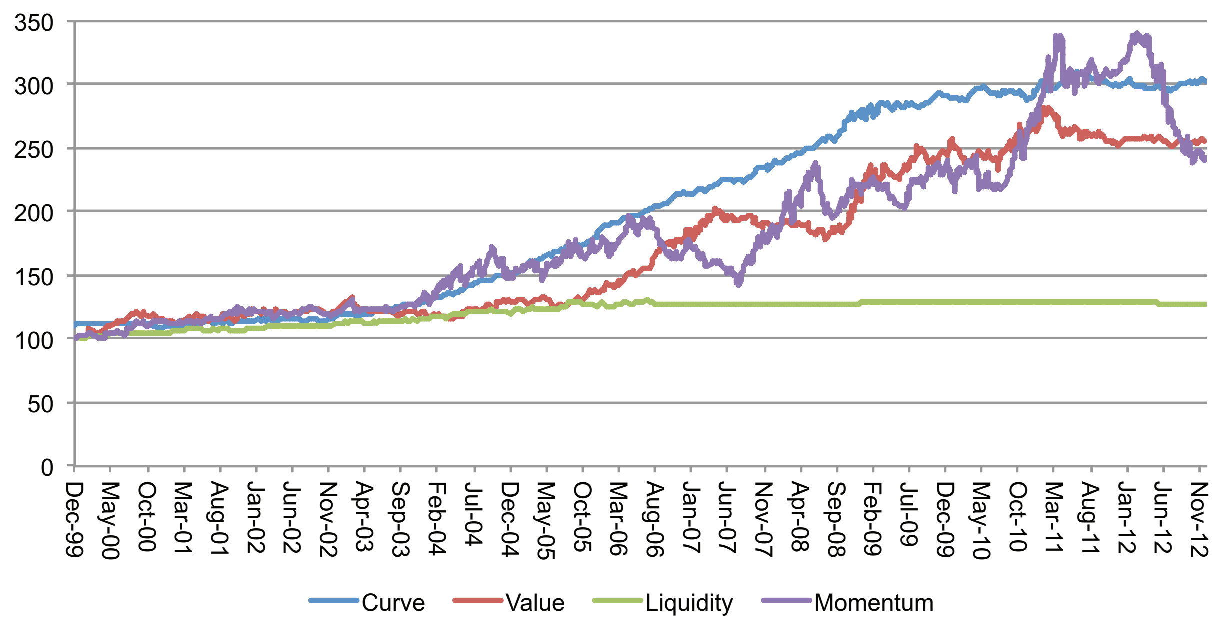

Exhibit 6a: Historical Performance of Systematic Commodity Factors

	Curve Factor	*Value Factor*	*Momentum Factor*	*Liquidity Factor*	*S&P GSCI Light Energy*
Curve Factor	1	0.145	0.128	0.055	-0.056
Value Factor		1	0.108	0.056	-0.017
Momentum Factor			1	0.287	0.428
Liquidity Factor				1	0.250
Broad Index					1

Exhibit 6b: Correlation of Matrix of Commodity Risk Factors

strategies allow commodities on a downward trend to be shorted, and this may generate additional value for the strategies.

It should be borne in mind that factor returns do not represent a source of riskless return, and can sometimes experience significant drawdowns (see Figure 6c). It is simply another way to construct an investment portfolio.

Having discussed the factors individually, we proceed to test the idea of combining them using two weighting schemes. For the purpose of this exercise, we look at the risk-weight and equal-weight approaches. Figures 6d and 6e present the results of the analysis and show that both strategies have outperformed the benchmark index on an absolute basis. However, despite recent underperformance, the risk-weight has performed better overall because it has a lower level of risk, suggesting that there may be an advantage in properly managing risks when creating a factors portfolio. Overall, regardless of the strategy chosen, they both have a low correlation with the benchmark and may act as a good portfolio diversifier.

The last step consists in investigating the potential benefits of combining the risk-weight factors portfolio with two versions of long-only commodity indices. Based on three hypothetical multi-asset portfolios consisting of 50% equity, 30% fixed income, and 20% commodi-

	Curve Factor	*Value Factor*	*Momentum Factor*	*Liquidity Factor*	*S&P GSCI Light Energy*
Standard Deviation	3.22%	8.33%	13.88%[5]	2.13%	18.32%
Maximum Drawdown	-5.40%	-24.89%	-30.03%	-54.97%	-68.78%

Exhibit 6c: Annualized Volatility and Maximum Drawdown of Commodity Risk Factors
Source: S&P Dow Jones Indices. Data from Dec. 31, 1999 to Dec. 31, 2012. Charts are provided for illustrative purposes. Past performance is not a guarantee of future results. Some data reflected in this chart may reflect hypothetical historical performance.

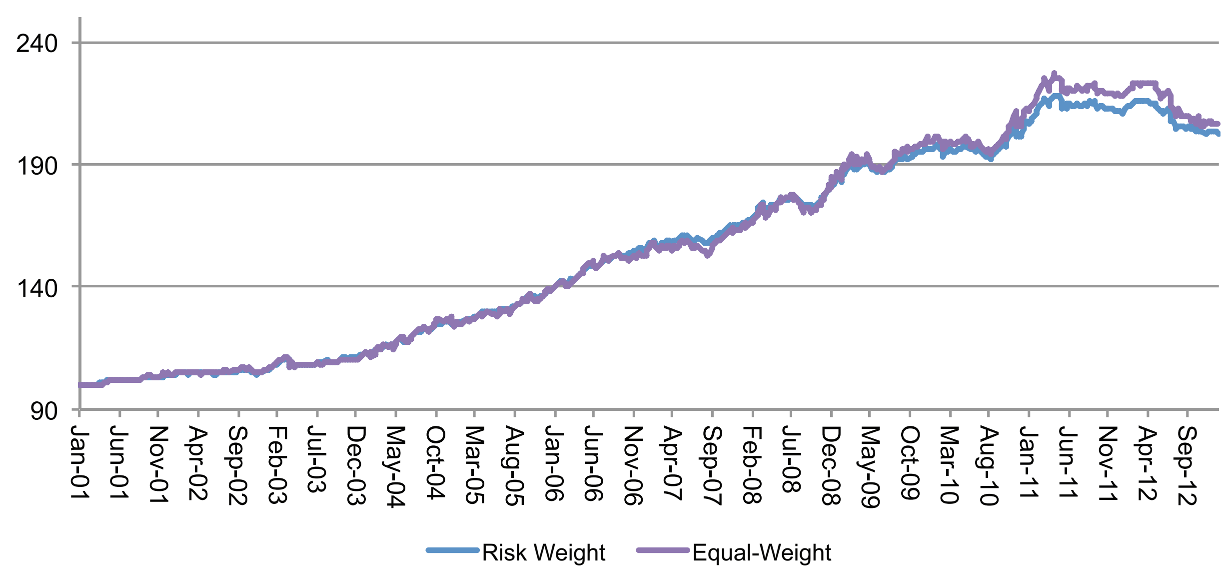

Exhibit 6d: Historical Performance of Compromise Factor Strategies

ties, the results in Figure 6f show that with a 20% commodity allocation, overlaying a portfolio of factors on to the investment portfolio improves the overall return. The outcome is even more encouraging when the risk-weight commodity index is used in lieu of the conventional long-only index.

3. Conclusion

Alternative beta strategies can serve a variety of different investment objectives, which may include reducing volatility or achieving tilts to systematic risk exposures. It is therefore essential for investors to examine whether these strategies meet their own investment objectives and risk-taking preferences.

Two main approaches to alternative beta are reviewed in this paper: the 'risk-based approach,' which entails reducing portfolio risk, and the 'factor-based approach,' which involves enhancing return through earning systematic risk premia with a focus on the latter. Whilst alternative beta is fairly well established in equity strategy investing, it is still a nascent concept in commodities. However, as a result of investors' pursuit of better diversified portfolios and a recognition that systematic risk factors explain the majority of returns, the development of commodity alternative beta products is gathering pace. This is not entirely unforseen as investors now view their investment opportunity in the context of risk premia, rather than individual asset classes. From our investigation in this study, there appears to be potential benefit in allocating into alternative beta strategies as part of a portfolio's commodity allocation, and we find that combining risk-based and factor-based commodity strategies has historically delivered higher return and lower risk than passive long-only strategies on their own.

Finally, it should be borne in mind that alternative beta strategies often take substantial active risks, which are largely driven by factor exposures. Factor returns can be volatile, and all alternative beta strategies can experience considerable drawdown at times. However, as

	Risk-Weight	*Equal-Weight*	*S&P GSCI Light Energy*
Return	6.07%	6.21%	0.47%
Risk	3.55%	4.65%	18.73%
Sharpe Ratio	1.00	0.88	-0.11
Correlation with S&P GSCI Light Energy	0.209	0.241	1.000

Exhibit 6e: Composite Strategies Return: Historical Annualized Risk and Return

	S&P GSCI Light Energy Index	*S&P GSCI Light Energy Index + Factors Overlay*	*S&P GSCI Risk Weight Index + Factors Overlay*
Annualized Risk and Return of the Commodity Allocation			
Return	2.2%	8.2%	11.3%
Volatility	18.1%	19.3%	13.6%
Sharpe Ratio	-0.01	0.31	0.66
Annualized Risk and Return of 50% Equity / 30% Fixed Income / 20% Commodity Portfolio			
Total Return	4.4%	5.6%	6.1%
Volatility	11.5%	11.6%	10.8%
Sharpe Ratio	0.19	0.29	0.36

Exhibit 6f: Combining Different Commodity Allocations in a Multi-Asset Portfolio
Source: S&P Dow Jones Indices. Data from Dec. 31, 1999 to Dec. 31, 2012. Charts are provided for illustrative purposes. Past performance is not a guarantee of future results. Some data reflected in this chart may reflect hypothetical historical performance.

Endnotes

1. The S&P GSCI Energy Total Return Index went up by 101% between December 1999 and December 2012.

2. Our analysis shows that the return spread between the first and fourth quartile is about 40 percent per year, when commodities are ranked by their relative futures basis.

3. The source of this demand is contentious. Some commentators argue that it comes from real demand in the economy; others believe it is related to speculative demand brought about by cheap metal financing. [Kaminska, 2011]

4. Estimate for the year 2012, published on the S&P Dow Jones Indices website.

5. It should be noted that because momentum strategies take both long and short positions on different commodities, it is not market neutral; hence it explains why this factor is higher than the rest of the factors.

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