| Monthly |

Commodity Compass

Finding beta – What exactly is the “commodity market”?


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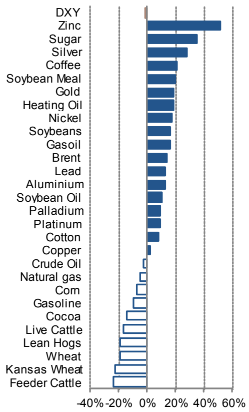


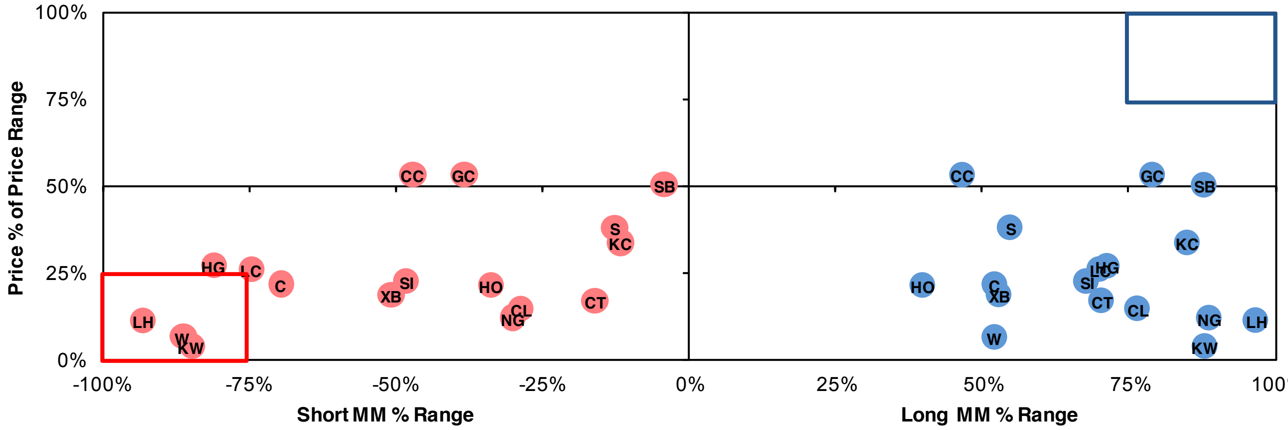
In this publication, we develop a methodology to define and isolate the “commodity market” risk and return profile – an abstract yet central element in tactical asset allocation. While it has become customary to refer to the market as “beta” and to proxy the commodity market with broad commodity indices such as the S&P GSCI and BCOM, our analysis shows that investors seeking to isolate the market return in either long only or long/short alpha strategies are in effect failing to rigorously do so.

In order to define the “commodity market”, we undertake PCA on the 24 commodities. From a methodological level, we provide a thorough but accessible explanation of the statistical apparatus. In application, we isolate and define the “commodity market”, quantify the level of systemic risk over time and identify the key drivers.

We show that that the drivers of the “commodity market” are more diversified than suggested by the composition of the S&P GSCI index. The implications are critical: in alpha strategies for example, in which investors short the market portfolio, using the S&P GSCI in lieu of the market portfolio fails to perfectly isolate systemic risk. Beta return is imperfectly neutralized, and alpha returns are equally eliminated.

We introduce a new section this month: Dry Powder analysis – insights into positioning.

Figure 1.1 – The SG Overbought/Oversold Indicator. Commodities in the oversold (red) box are vulnerable to short-covering and commodities in the overbought (blue) box are vulnerable to profit-taking



The SG OBOS indicator defines and identifies “oversold” (“overbought”) commodities on a weekly basis as those that are lying at the intersection of extremes in both short (long) positioning and price weakness (strength). The “oversold” (“overbought”) box is shown in red (blue) in Figure 1.1. Commodities within the “oversold” (“overbought”) box are trading in the bottom (top) 25% of their price range and have a short (long) position (calculated as the short [long] Money Manager [MM] open interest [OI] as a percentage of total OI [source: CFTC COT report]) in excess of 75% of the historical maximum. These commodities are vulnerable to short-covering (profit-taking). Please refer to the following publication for details about the indicator and historical performance: Commodities Compass - Identifying “oversold” commodities – the intersection of two extremes.
Source: SG Cross Asset Research/Commodities, Bloomberg.

Finding beta – What exactly is the “commodity market”?

Out of all the asset classes, the question of “what exactly is the commodity market?” is probably most relevant to commodities. Furthermore, with the recent growth in market-neutral and risk-premia investment strategies in recent years, answering this question has become ever more critical. In modern portfolio theory, beta is defined as the sensitivity of a security (or portfolio thereof) to the market volatility, i.e. its sensitivity to systemic risk. More broadly, beta has also come to denote the market and its risk-return characteristics – in this publication we refer to beta and the market interchangeably. In the case of commodities however, being an investable asset class of generally less than 30 individual markets, beta is often ill-defined or assimilated to broad market indices such as the S&P GSCI or BCOM. In many cases, these indices have become entirely synonymous with the commodity market.

In defense of this practice, in the case of commodities – a very complex asset class, with significant diversity between the individual commodities and little commonality in terms of price drivers across the asset class - there has been little choice. It has been argued that, for an asset class with so few individual constituents, it is perhaps acceptable to proxy the market with these indices. From a fundamental perspective however, there is no reason to believe that the sugar market should be influenced by the live cattle market which also should not be influenced by the lead market which should not be influenced by the natural gas market and so on and so forth.

Table 1: 24 S&P GSCI ER indices

SPGCCCP	Cocoa
SPGCCNP	Corn
SPGCCTP	Cotton
SPGCKCP	Coffee
SPGCSBP	Sugar
SPGCKWP	Kansas wheat
SPGCWHP	Wheat
SPGCSOP	Soybeans
SPGCLCP	Live cattle
SPGCLHP	Lean hogs
SPGCFCP	Feeder cattle
SPGCIAP	Aluminium
SPGCICP	Copper
SPGCIKP	Nickel
SPGCILP	Lead
SPGCIZP	Zinc
SPGCBRP	Brent
SPGCCLP	Crude oil
SPGCGOP	Gasoil
SPGCHOP	Heating oil
SPGCHUP	Gasoline
SPGCNGP	Natural Gas
SPGCGCP	Gold
SPGCSIP	Silver

Source: SG Cross Asset Research

In this month’s publication, we challenge this practice and attempt to define systemic risk in commodities or the commodities market more sensibly. This will allow investors to better refine their exposure to the asset class’ risk and return profile. Furthermore, the potential of commodities to contribute to an investor’s portfolio in specific pure alpha and long/short strategies may not be optimal when the short leg (generally required to be the market) is executed through the main indices. For example, the S&P GSCI is heavily skewed to the energy sector, and is likely to bear much energy-related idiosyncratic risk.

Our investigation more sensibly defines the “commodities market” and therefore identifies a new commodity market factor – or beta – which is characterized by a more balanced basket of commodities than found in the major commodity indices. We provide insights into the composition of this beta and track its evolution over time. We propose an alternative market (beta) portfolio and compare its performance to the S&P GSCI.

In our quest to uncover beta, we undertake principal component analysis (PCA) on the 24 S&P GSCI commodity excess return mono indices. These cover 6 energy, 11 agriculture and livestock and 7 base and precious metals. Prices for all 24 commodities are available from 2002 onwards. In this publication, our objective is twofold: on a methodological level, we thoroughly describe PCA and its statistical proprieties. In application, we use this statistical apparatus to reveal the systemic commodity risk profile. This approach allows us to make a number of important claims regarding the composition of returns – the alpha and beta embedded in the returns of the constituent commodities.

This methodology also provides additional insight into the other sector-level drivers of commodity returns and highlights in a much subtler way the cross-correlations between returns. Our methodology affords us the answers to a number of questions, including:

- What exactly is the commodities market? What level of volatility is structurally embedded in commodities as an asset class?

- How does the commodity market factor profile or beta evolve over time? How stable is it?
- How much does each commodity contribute to beta?

PART 1: principal component analysis

Principal component analysis (PCA) has grown in popularity in recent years in almost every discipline imaginable and has proven to be an important statistical tool used in almost all areas of quantitative finance.[1] For example, portfolio managers' employ the methodology to allocate funds amongst different assets and also assets classes, interest rate structurers employ the technique to model the yield curve and analyze its changing shape. Rates and fixed income traders use the methodology to hedge portfolios, equity traders use the algorithm to buy and sell stocks and FX algorithmic traders use this to generate price signals. PCA is also used in many other disciplines from biology, physics, engineering, and economics to software development and internet search engines. For us, in our Commodity Compass publications for example, we use a proprietary PCA model to attribute commodity price variance between fundamental and non-fundamental drivers. In our Energy Skew Drivers publication we use the PCA algorithm to screen for over and underpriced options using the last 3 year's covariance structure.

In part 1 of this editorial, we thoroughly describe the statistical methodology, and interpret the results in a practical way.[2] This section is designed to provide a technical overview of principal component analysis such as to demystify its application, addressed in the second part of this publication. In so doing, we first address the objectives of PCA, and then show how to derive PCA with two trivial 2-dimensional examples using related commodities. We then extend PCA to the 24 commodity S&P GSCI excess return (ER) mono indices.

Concepts and objectives

> The central idea of principal component analysis is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible the variation present in the data set. This is achieved by transforming to a new set of variables, the **principal components** (PCs), which are **uncorrelated** and which are ordered so that the first few retain most of the variation present in all of the original variables.
>
> *Jolliffe (2002)*

PCA is not in and of itself a predictive model, but rather a procedure which rearranges data in order to uncover commonalities. For example, when applied to the 24 GSCI ER mono indices, PCA produces 24 differently weighted baskets of the 24 mono indices; with each basket being a linear combination of the original variables. These baskets (or components) have a number of tractable statistical proprieties which make them particularly useful for subsequent analysis. Each component explains a fraction of the variability of the underlying dataset, such that the sum of the component variability is equal to the aggregate variability of the underlying data (**Figure 1**).

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[1] In 1901, Karl Pearson published a paper titled "On Lines and Planes of Closest Fit to Systems of Points in Space." *Philosophical Magazine* Series 6 2(11):559 – 572. 1901. The paper was an exploration of ideas concerning an affine space that best fits a series of points, where the fit is measured by the sum of squared orthogonal distances from each point to the space. Pearson's work is often considered to have laid the foundations of PCA. It was later developed (and named) by Harold Hotelling in the 1933. Hotelling, H. (1933). "Analysis of a Complex Statistical Variables into Principal Components." *Journal of Educational Psychology*, 24, 417 – 441, and 498 – 520.

[2] For a comprehensive reference for the PCA methodology interested readers are directed to I.T Jolliffe, "Principal Component Analysis", Second Edition, Springer Series in Statistics.

Figure 1 – Principal component decomposition rearranges data to preserve total variability

Input	Cocoa	Corn	Cotton	Coffee	Sugar	...	Gasoline	Nat. Gas	Gold	Silver	TOTAL
annualized variability	9.24%	9.04%	7.93%	9.40%	10.08%	...	12.70%	22.33%	3.44%	11.01%	221%

Principal Component Decomposition

Output	PC1	PC2	PC3	PC4	PC5	...	PC25	PC26	PC27	PC28	TOTAL
annualized variability	73.93%	27.99%	21.17%	17.20%	11.33%	...	0.56%	0.50%	0.45%	0.43%	221%
% of total variability	33.42%	12.65%	9.57%	7.77%	5.12%	...	0.25%	0.22%	0.21%	0.19%	100%
cumulative	33.42%	46.07%	55.64%	63.41%	68.53%		99.12%	99.38%	99.60%	99.81%	100%

Note: throughout the editorial, we use the term variability to denote variance (i.e. the average squared deviation from the mean). We prefer this term over variance to highlight the fact that total variability is defined as the sum of the variances of each constituent (e.g. 9.24% + 9.04% + ...) – not the variance of the blended constituent returns. Because the S&P GSCI constituents are not independent (i.e. they are correlated), the two metrics differ. The term total risk is also sometimes encountered in financial literature.
Source: SG Cross Asset Research/Commodities

To emphasize the fact that principal component decomposition produces linear combinations of the original data with no informational loss, we note that the aggregate variability of the 24 SPGC indices is 221% per annum. The aggregate variability of the 24 components is likewise equal to 221% per annum. We will see in a subsequent section how to derive these.

The usefulness of principal component decomposition thereafter lies in the fact that most of the dataset variability – the information – can be concentrated into a few components. The components are ordered by their variability, such that the first component explains the highest fraction of total dataset variability. In the above example, we observe that the first component explains 33.42% of the total dataset's variability. Cumulatively, the first 5 components jointly capture 68.53% of the total variability. The last four components on the other hand capture less than 1% of the total variability. The terms principal component and component are synonymous – the principal components generally refer to those that explain the greatest percentage of overall variability.

Because most of the dataset's variability is now concentrated in a few components, we can decide to dispose of the components that capture little or no information ("noise"). On the other hand, the components that cumulatively capture the highest fraction of variability (i.e. information) are deemed more important – these are the **principal components**.

The number of components to keep depends on the objectives. The three main strategies to do this are:

1. keep **k** components, for example 3 (k = 3) - this strategy makes sense if the purpose of principal component analysis involves quantifying the relative informational weight of predetermined factors (for example the first 3);

2. keep the **k** first components such that they jointly explain no less than **x%** (e.g. 70%) of total variance – this strategy is suitable when the principal components feed into other models which proxy the underlying data with the principal components (e.g. factor analysis). The objective here is to reduce the number of inputs in the subsequent computations;

3. keep any component whose variability is greater than 1/n, where *n* represents the number of inputs (e.g. 24 for our purpose). The idea here is to keep the components that capture more information (i.e. variability) than the average variability of the 24

original variables. If, for example, the data contains a set of variables having large within-group correlations, but small between-group correlations, then PCA will generally produce one component verifying this condition.

Besides concentrating the dataset's variability into a few components, the components are also **orthogonal** to each other – meaning that there are perfectly uncorrelated. As such, the principal components can be used as independent variables in multiple regression estimation without problems such as multicollinearity.

Perhaps most importantly, principal components can capture and quantify effects which are not otherwise easily observable. For example, from the 24 S&P GSCI excess return mono indices, PCA can identify the distribution and localization of systemic risk – attributes that neither the benchmark (the S&P GSCI index) nor for example the equal aggregation of the constituents can effectively reproduce (see part 2 of this editorial).

In the following section, we show how to operationally derive the principal components on a trivial 2-dimensional example.

Deriving PCA on a 2-dimension dataset: the crude oil market

Our first example is a trivial one, but it enables us to derive the principal components and to visualize the raw and the transformed data simultaneously. The point here is not to demonstrate the usefulness of PCA on a two-dimensional dataset – it is frankly rather limited – but rather to illustrate its operational implementation and results. **Readers more interested in the application of PCA in our current context of defining and isolating the "commodity market", should turn directly to part 2 of this editorial.**

Suppose we want to aggregate the returns from Brent and WTI into a single oil component, to capture the general price-level volatility of the crude oil market. For the purpose of this simple model, we posit that crude oil returns are dominated by an inherent price (value) component, which is a general function of the global crude market's fundamentals such as supply and demand. By extracting this fundamental value component from North-American WTI and European Brent, PCA essentially removes inter-regional market dynamics – the geographic spread component. Given the high substitutability of WTI and Brent, we posit that the geographic spread component explains little of the crude-oil return volatility. Neither a linear regression nor correlation analysis would effectively capture these.

The first step involves **normalizing** the prices. PCA is sensitive to the scale and unit of the data it seeks to transform. In the present case, we compute the log-returns for Brent and WTI. Depending on the data, a further normalization step would involve scaling the means to 0 and the variance to 1 (i.e. computing Z-scores) – but in our present case, we do in fact want higher embedded variances in certain commodities to influence the matrix decomposition and isolation of the components. Unsurprisingly, we observe that weekly returns for WTI and Brent are highly correlated (**Figures 2 and 3**, sample weekly correlation of 94.88% for the period 2005-2016).

Figure 2 – Weekly log-returns for WTI and Brent (2005 – 2016)

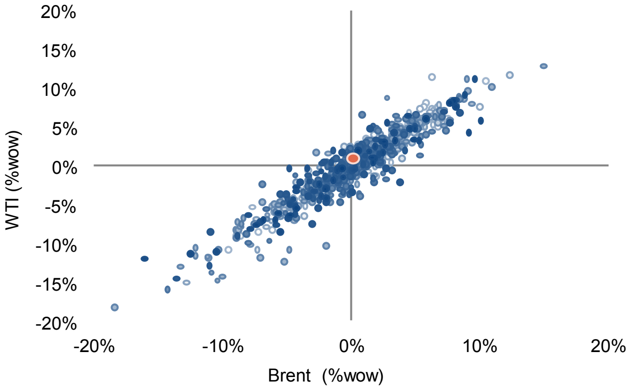
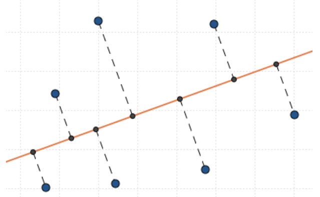


Figure 3 – Statistical proprieties of WTI and Brent log-returns

	WTI	Brent
no. of weeks	771	771
avg. %wow log-return	0.04%	-0.08%
annualized volatility	32.31%	34.29%
Augmented Dickey Fuller test	**WTI**	**Brent**
test statistic	-7.9408	-7.9409
p-value	0.0000	0.0000
Covariance matrix	**WTI**	**Brent**
WTI	0.226%	0.202%
Brent	0.202%	0.201%
Correlation matrix	**WTI**	**Brent**
WTI	100.00%	94.88%
Brent	94.88%	100.00%

Darker points are more recent; orange point is most recent (week to 14 Oct 2016). Results from the Augmented Dickey Fuller test confirm each series are stationary as each series has been transformed to ensure stationarity in analysis (by taking log returns).
Source: SG Cross Asset Research/Commodities

Figure 4 - PCA involves minimizing the orthogonal distances (dotted lines)



For illustrative purposes only
Source: SG Cross Asset Research

An important requirement for PCA is that the input data is stationary. A stationary time series is one whose statistical properties such as mean, variance, autocorrelation, etc. are all constant over time. This is not a trivial assumption to make for commodity returns given the existence of price cycles and persistent trends. We test the log-returns for stationarity using the Augmented Dickey Fuller Test and reject non-stationarity in the log-returns (**Figure 3**, p-value = 0.0000 for both WTI and Brent).

PCA then involves finding the two (as we only have two variables in this example) lines ("components"), orthogonal to each other, which individually minimize the orthogonal distance of the data project on the lines (see **Figure 4** left for an example). Mathematically, the solution to this maximization (maximizing the variability of the dataset) problem involves finding the sorted **eigenvalues** and **eigenvectors** of the covariance matrix[3]. It is customary to derive unit-length eigenvectors which leads to a simple Lagrangian optimization problem. The eigenvectors are then the coordinates of the component variables while the eigenvalues measure the variability of the components (lines).

Eigenvectors and eigenvalues

Let $COVAR = \begin{pmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,n} \end{pmatrix}$ denote the $n \times n$ covariance matrix. The eigenvector/eigenvalue matrix identity is captured in the basic equation:

$$Eigenvector \cdot COVAR = Eigenvalue \cdot COVAR$$

Since the $COVAR$ matrix is symmetric, the eigenvector can be found using the Jacobi eigenvalue algorithm.

Figure 5 shows the original WTI and Brent log-returns with the fitted components. The first component (dark orange line) captures most of the variability in the dataset. The second component (lighter orange line), **orthogonal** to the first, captures significantly less variability of the data. **Figure 6** quantifies this decomposition: the first component captures 97% of the

[3] The mathematical derivation can be found more explicitly at the following address: http://www.stat.columbia.edu/~fwood/Teaching/w4315/Fall2009/pca.pdf

dataset's variability, whereas the second component captures merely 3% of the variability (shaded cells in table).

PCA (factor) scores

We can then use the eigenvectors to compute the PCA **scores** (also known as "eigenportfolios") – these are the linear combinations of the original data using the eigenvectors as weights (**Figure 7**). Graphically, the PCA scores are a **rotation** of the original dataset, using the components (orange lines in **Figure 5**) as their new axes. As confirmed by the correlation table, the computed scores appear uncorrelated to each other in **Figure 7**.

Figure 5 – Original dataset with two principal components axes

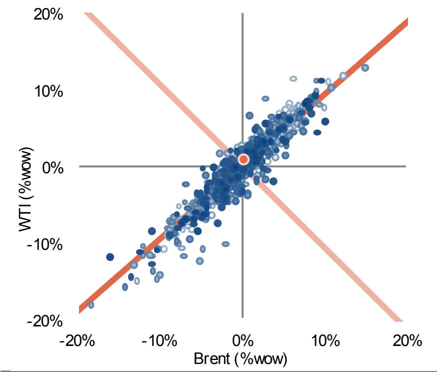
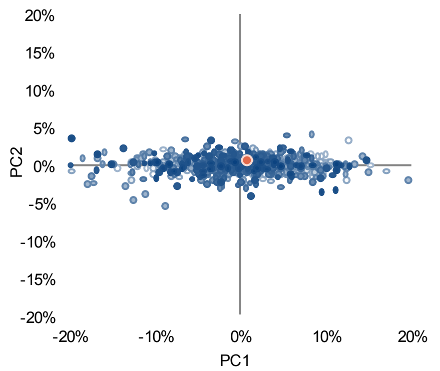


Figure 6 – Eigenvalues, eigenvectors and loadings

	PC1	PC2	Total
Eigenvalue	0.0042	0.0001	0.0043
%total variability	97.45%	2.55%	100%
Eigenvectors	**PC1**	**PC2**	
Brent	0.685	-0.729	
WTI	0.729	0.685	
Vector length	1.000	1.000	
Loadings	**PC1**	**PC2**	
Brent	0.0442	-0.0076	
WTI	0.0470	0.0071	
Scores	**PC1**	**PC2**	**Total**
Variability	0.0042	0.0001	0.0043
Correlation	**PC1**	**PC2**	
PC1	1.00	0.00	
PC2	0.00	1.00	

Figure 7 – Rotated dataset (PCA scores)



Axes scales are intentionally left equal to each other. Darker points are more recent; orange point is most recent (week to 14 Oct. 2016). The first eigenvalue (0.0042) is the variance of the first principal component. **Vector lengths** are computed by summing the squared eigenvectors ($0.685^2 + 0.729^2$). Because of the way PCA is mathematically set-up, these are equal to 1. We can map each observation (i.e. blue dot in Figure 5) in the original dataset a **PCA score** (i.e. blue dot in Figure 6). For example, for week to 14 Oct 2016 (orange dot), the WTI/Brent log-returns are {0.15%, 0.92%}. The score for the week to 14 Oct 2016 {0.77%, 0.52%} is then computed as the product of the eigenvectors with the returns (0.15% x **0.685** + 0.92% x **0.729** = 0.77% and 0.15% x **-0.729** + 0.92% x **0.685** = 0.52%). Loadings are computed as the eigenvectors scaled by the square root of the eigenvalues (e.g. 0.685 x $\sqrt{0.0042}$ = 0.0442). The variability of each score time series is equal to its eigenvalue: for example, the variance of the first PC is 0.0042, which is equal to its eigenvalue.
Source: SG Cross Asset Research/Commodities

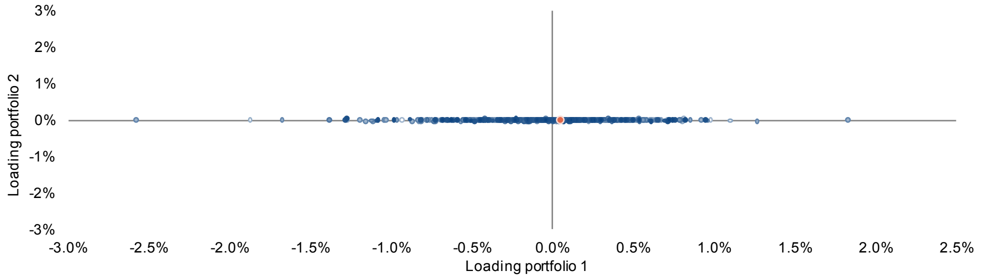
PCA (factor) loadings

Principal component analysis allows us to split the raw data into separate components and to significantly filter noise. In so doing, PCA splits the variability of the original dataset (via its covariance or correlation matrix) into levels of variability (the eigenvalues) and directions or weights for each variable (eigenvectors). Each component explains a proportion of the dataset's total variability (its eigenvalue) and the weights attributed to each component variable (e.g. WTI and Brent) give a sense of the sources of variability – its directionality (eigenvector).

These two features – level and directionality - can be combined together to produce what are known as the **PCA loadings**. These loadings are the eigenvectors scaled by the square root of their respective eigenvalues - in other words, it scales the eigenvectors by the component's contribution to the overall variability.

Figure 8 plots the returns of the **loading portfolios**. Loading portfolios are constructed by weighting the original data by the above-computed loadings. Consistent with the relative eigenvalues, the variability of the second dimension (y-axis) is considerably muted compared to the first (x-axis). This also highlights the data reduction ability of PCA – essentially a set of data with $\{x: y\}$ coordinates has been reduced or simplified to a data set with positive and negative deviations from a single axis.

Figure 8 – Loading portfolio returns



Axes scales are intentionally left equal to each other. Darker points are more recent; orange point is most recent (week to 14 Oct 2016). Each of the 771 original observations (i.e. week) maps to one of the 771 loading returns.
Source: SG Cross Asset Research/Commodities

Table 2 – Contributions to the variability of the variables

	PC1	PC2
WTI	47%	53%
Brent	53%	47%

Source: SG Cross Asset Research

It should be noted that the value of the loading portfolio returns are in themselves meaningless. Rather, it is their statistical proprieties which endow them with meaning: by construct, the sum of squared loadings of each variable is equal to that component's eigenvalue, such that these squared loadings identify the contribution of a component variable (e.g. Brent or WTI) to the component's variability. **Table 2** summarizes this result for Brent and WTI. We observe that the sources of variability of the two variables are relatively balanced – this is to be expected given the high degree of substitutability of the two commodities as well as their market structures.

Interpreting PCA output

Unlike factor models derived from empirical economic phenomena, PCA is purely statistical and its usefulness hinges on the ability to interpret the output. As described in the literature, the components need not make sense, although it is often the case that they do.

In our present example, we can interpret the first component as capturing the inherent price (value) dynamic of the crude oil market as a whole. Stated differently, the first component captures the fundamentally-driven volatility of the crude market. More generally, the first component should capture the **market factor** of the input variables: indeed, the first component is computed such as to maximally capture the variability of the dataset – i.e. the tendency of commodities to move together as an asset class.

The subsequent components on the other hand are computed to capture as much variability as possible, holding the market factor orthogonal. These therefore capture sector factors. In our present example, the second component could be regarded as the geographic spread component, i.e. the volatility of the crude oil returns driven by the intra-market tensions and the inability to arbitrage geographic spreads instantly (due, for example, to logistics separating the two markets). Given the magnitude of this component's eigenvalue however, we can disregard it altogether as noise. Logically, and given the fact that the crude oil market is a globalized and integrated market, the price (value) component dominates the latter component: 97% of the variability of WTI and Brent prices can be attributed to their co-movement, i.e. the broad movements of the crude-oil market.

What we have done here is to reduce the number of dimensions in our initial dataset (2D), generating a one-dimensional dataset capturing the essence of the information. We have filtered out the noise related to the geographic spread component. This trivial example served the purpose of illustrating the methodological steps required to conduct PCA. As an additional illustration, we conduct a similarly simple PCA analysis on the gold-silver complex and summarize the results below.

Deriving PCA on a 2-dimension dataset: the precious metals market

The crude oil market is a highly integrated market, characterized by a high degree of commodity substitutability. As such, it is not surprising to find that PCA identifies the price (value) component as being overwhelmingly dominant (97%). Both Brent and WTI contribute in a balanced way to the variability (47% and 53%), highlighting the similar price-volatilities of the two products. We briefly illustrate again the mechanisms of PCA on another two-dimensional dataset, namely the gold-silver complex.

Unlike Brent and WTI, gold and silver exhibit a lower degree of substitutability. Over the period 2002-2016, we find a cross-correlation of log-returns of 78%, a relatively lower figure than the crude oil products. The results of the PCA are summarized in **Figures 9 to 14**. We plot the week-on-week log returns with the fitted component axes in **Figure 9**. The first component (darker orange line in Figure 9) concentrates most of the variability compared to the second component (lighter orange line). The rotated dataset in **Figure 10** makes this visually obvious: while points are mostly scattered in the +/- 10% range along the first component axis (horizontal line), variability is mostly contained in the +/- 5% range along the second component axis.

Numerically, we find that the first principal component captures 92% (eigenvalue of 0.0026; sum of all eigenvalues 0.0028) of the common variability of the dataset (**Figure 11**). We can interpret this component as the "*preciousness"* (sic) factor embedded in the precious metals market, i.e. its market factor. Although relatively lower than the crude oil market, this nonetheless signifies that volatility in one variable (e.g. gold) is generally associated with the volatility in the other variable.

Looking at the composition of the eigenvectors and the loadings' profile, we observe that silver is a non-negligible contributor to the volatility of the precious metals markets. Silver drives 81% of the first component's variance (**Figure 13**). This is in line with intuition: silver exhibits higher volatility (33% versus 19% for gold). And because we purposely did not Z-score the log-returns, silver should intuitively be a more significant driver of total variability.

Figure 9 – Gold and silver week-on-week returns, 2002-2016

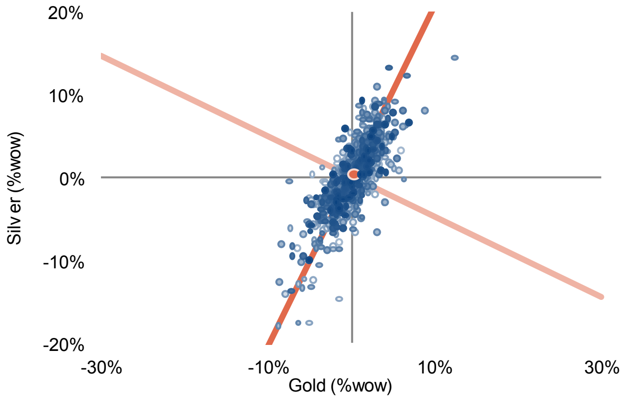
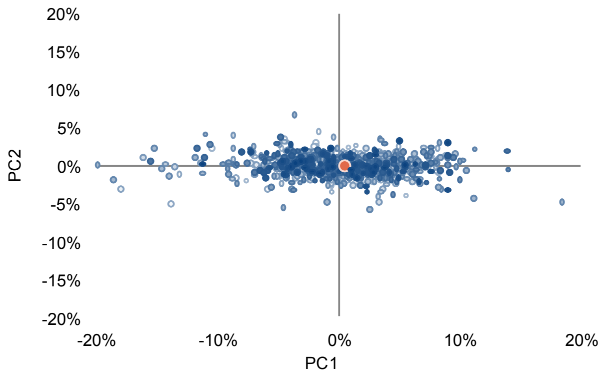


Figure 10 – Eigenportfolio returns, based on gold and silver decomposition, 2002-2016



Note: the sizing of the chart may result in visually non-orthogonal components. Darker points are more recent, orange dot is most recent (week to 14 Oct 2016). Eigenportfolio returns (also known as scores) in Figure 10 are visually a rotation of the original dataset.
Source: SG Cross Asset Research/Commodities

Figure 11 – Summary statistics of the gold and silver principal component decomposition

	Gold	Silver
no. of weeks	771	771
avg. %wow log-return	0.15%	0.13%
annualized volatility	18.55%	33.18%
Augmented Dickey Fuller stationarity test	**Gold**	**Silver**
test statistic	-28.13	-27.56
p-value	0.0000	0.0000
Covariance matrix	**Gold**	**Silver**
Gold	0.07%	0.09%
Silver	0.09%	0.21%
Correlation matrix	**Gold**	**Silver**
Gold	1.00	0.78
Silver	0.78	1.00

	PC1	PC2	Total
Eigenvalue	0.0026	0.0002	0.0028
% total variability	92%	8%	100%

Eigenvectors (Figure 12 and 13)	PC1	PC2
Silver	0.436	-0.900
Gold	0.900	0.436
Loadings (eigenvectors $\times \sqrt{\text{eigenvalues}}$)	**PC1**	**PC2**
Silver	0.022	-0.013
Gold	0.046	0.006
Contributions to variability (see Figure 14)	**PC1**	**PC2**
Silver	81%	19%
Gold	19%	81%

Source: SG Cross Asset Research/Commodities. Results from the Augmented Dickey Fuller test confirm each series are stationary as each series has been transformed to ensure stationarity in analysis (by taking log returns).

Figure 12 – Eigenvector of the first component

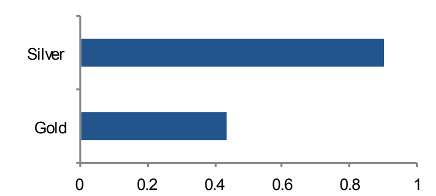


Figure 13 – Eigenvector of the second component

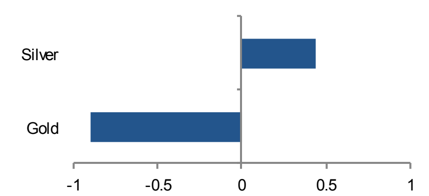
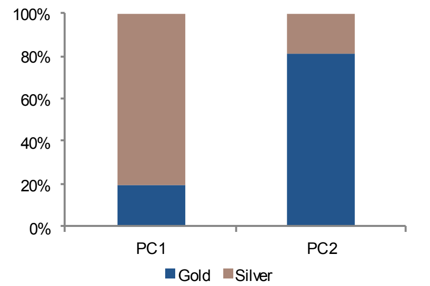


Figure 14 – Contributions to component volatility



Source: SG Cross Asset Research/Commodities

The second component is dominated by gold (81%) – as gold is traditionally more of a safe haven asset than silver, we could interpret this component as a "safe haven-ness" factor.

As with the crude oil market, applying PCA on a two-dimensional dataset has limited added-value. It however allows us to intuitively understand the principles and visualize the transformation. In the following section, we deploy PCA on a broader selection of data points and illustrate the way in which results can be given richer meaning.

PART 2: Finding beta – What exactly is the "commodity market"?

Investors have used benchmark indices as a cost-effective vehicle to invest in the asset class. Commodity benchmark indices such as the S&P GSCI have many advantages such as giving investors exposure to commodities in the rough proportion that they flow through the global economy, but they also suffer from a number of structural weaknesses: by weighing commodities by world production, the S&P GSCI attempts to mimic market-cap equity indices but simultaneously eliminates a lot of the diversification potential of the commodity asset class. **In the second part of this publication, we propose a new methodology to define and isolate the "commodity market" risk and return profile in order to reveal a more balanced and intuitive commodity market factor or beta, and examine its structural changes over time**. Building on these results, we propose a new dynamic commodity market portfolio and compare its performance to the S&P GSCI benchmark index.

Our methodology relies on the use of PCA, explained in the **Part 1** of this publication. We noted above that, by construction, the first principal component captures the largest amount of the dataset's common variability. Indeed, the first component maximally captures the variability of the data at hand, i.e. the tendency of commodities to move together – essentially the commodity market factor or beta.

We apply principal component decomposition on the 24 S&P GSCI commodity excess returns indices (see **Table 1** for list of constituents). An analysis of the cross-correlations would not suffice to evidently easily uncover the return commonalities across the commodity universe. **Figure 15** shows the cross-correlations of the 24 commodities: with 276 pairs to analyze, the problem of information overload is evident. We summarize the eigenvalues of the first 10 components of the full-period (2002-2016) in **Figure 16** below. The first component captures 33% of the total variability, more than three times that of the second component. Stated differently, 33% of the variability of the commodity excess returns is common to all of the asset class' constituents.

Consistent with the literature on PCA, we find that that the first eigenvector exhibits weights of the same sign (**Figure 17a**). Noticeably, the first eigenvector is skewed to the energy and metals sectors, with less weight given to the grain and livestock sectors. What this means is that more of the systemic asset class volatility (beta) is found with the energy and metals sectors. Stated differently, **when the energy market undergoes a bout of volatility, the other commodities will tend to fluctuate concurrently**. The noticeable oddity is gold, but this is consistent with its own market specificity.

To interpret the second and third eigenvector, we need to scrutinize the weights attributed to the each vector. The signs of the eigenvector entries are irrelevant[4]; it is instead the **polarization** of groups of commodities that matter. While the first component captures the market factor or portfolio, the subsequent components capture specific sector risk factors (analogous to the Small Minus Big (SMB) or High Minus Low (HML) factors in the Fama & French 3-factor model for equities).[5]

[4] For example, the negative of an eigenvector is also mathematically an eigenvector

[5] E.F Fama and K.R French, "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics*, 33 (1993), 3 - 56.

Figure 15 – Commodity cross correlations. Figures in diagonals represent each commodity's average cross correlation with the 23 other commodities

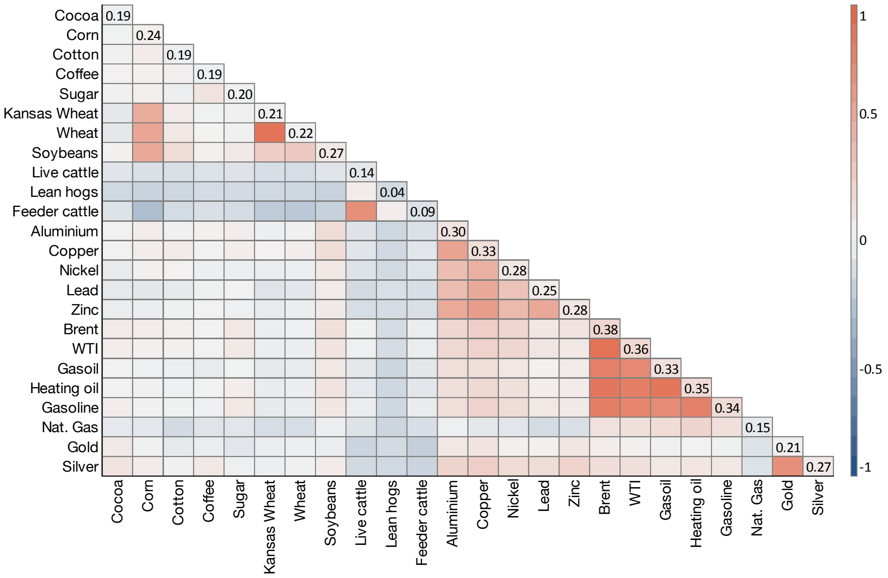
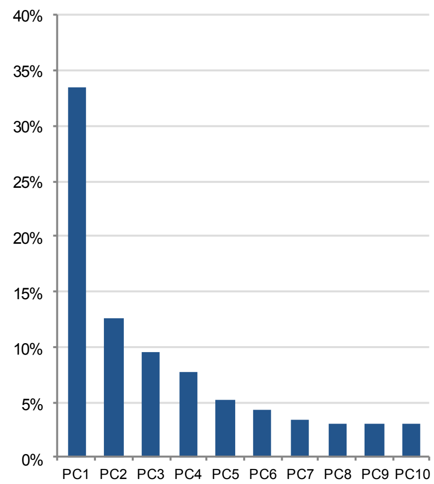


Figure 16 – Eigenvalues of the 10 first principal components (% of total variability)



Figures in diagonals represent each commodity's average cross correlation with the 23 other commodities. For example, the average correlation of cocoa with the 23 other commodities is 0.19. The energy complex exhibits the highest levels of correlation (darker shades of red). Figures close to 0 imply no correlation, while figures close to 1 (resp. -1) imply high positive (resp. negative) correlation. These are is darker shades of red (resp. darker shades of blue).
Source: SG Cross Asset Research/Commodities

The second component can be interpreted to capture the energy sector as a source of risk (**Figure 17b**). Likewise, the third component pitches the (base and precious) metals against the grains sector as a risk factor (**Figure 17c**).

Jointly, the first three components explain more than 55% of the total variability. The first 6 components jointly isolate 73%, while including 10 components would capture 85% of the variability. In this way, PCA has reduced the number of dimensions (down from 24) with little loss of information. As we discussed in the first part of this publication, reducing our dataset dimensionality enables us to run multiple linear regression analysis by overcoming the multicollinearity problems - commodities being particularly correlated (e.g. within the energy sector).

In all of our Commodity Compass publications for example, we specifically use principal component regression (PCR) in our PCA to attribute commodity price variance between fundamental and non-fundamental drivers.

Figure 17a – 1st component

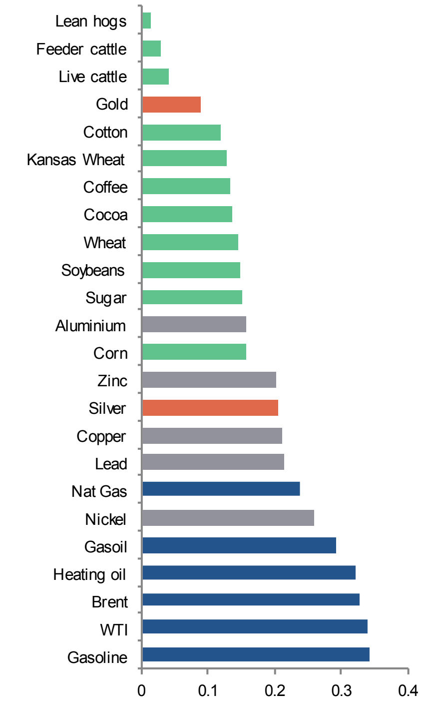


Figure 17b – 2nd component

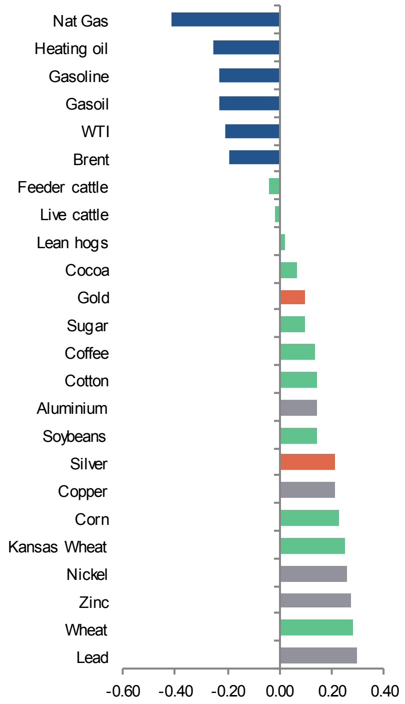
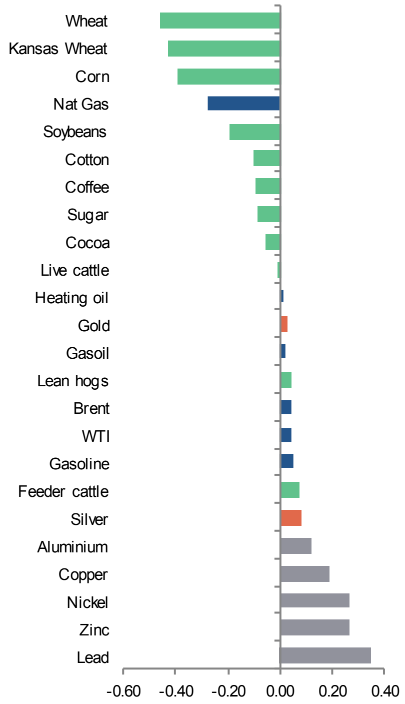


Figure 17c – 3rd component



Colours indicate subsector: agriculture and livestock base metals precious metals energy
Source: SG Cross Asset Research/Commodities

Composition of commodity market factor or beta

Importantly for our present analysis is the extent to which commodities' volatility is driven by the asset class as a whole – the systemic source of risk – rather than by the sector-level or unit-level dynamics. The first eigenvalue captures this metric (33%).

PCA further allows us to identify the sources of this systemic market risk. We compute the squared loadings of the first principal component. **Figure 18** graphs the contribution of each commodity to the variance of the first principal component. We note that the *sources* of systemic risk in the commodity market or beta portfolio are similar to the constitution of the S&P GSCI. For example, the 2017 weight of the energy sector in the S&P GSCI index is estimated at 56%[6]. This is comparable to the 58% level identified by PCA.

[6] http://us.spindices.com/documents/index-news-and-announcements/20161006-sp-gsci-rebalance-advisory-panel.pdf?force_download=true

Figure 18: Commodity contributions to systematic risk (% of beta portfolio variance)

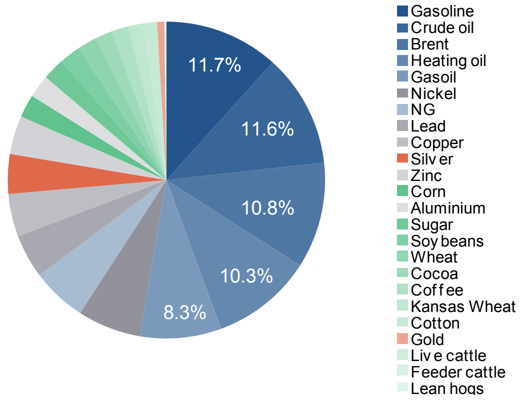
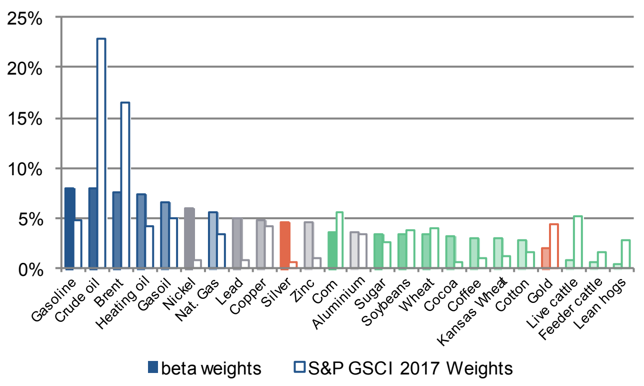


Figure 19: PCA beta weights versus S&P GSCI 2017 weights



Source: SG Cross Asset Research/Commodities, S&P

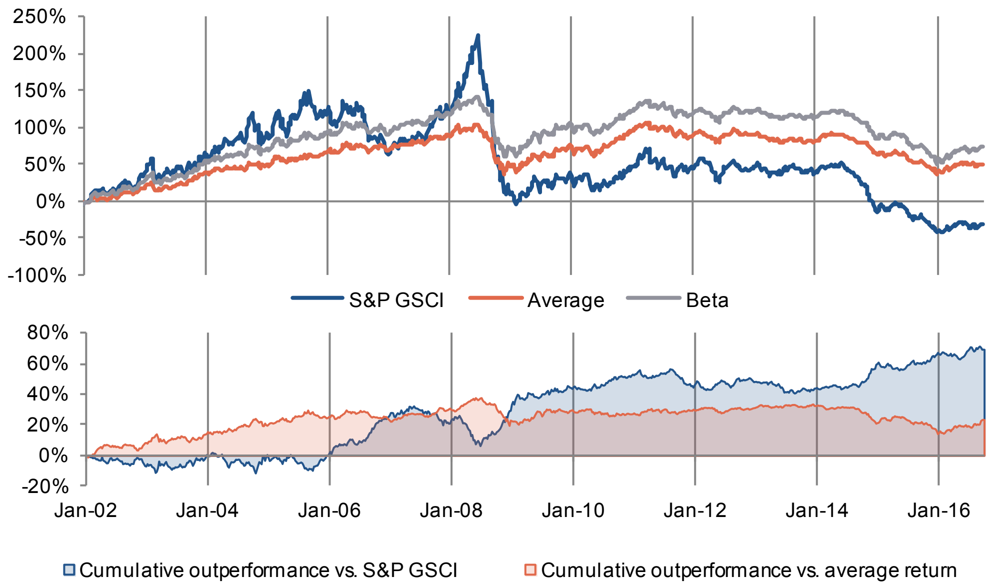
Figure 19 on the other hand compares the weights of the PCA beta portfolio with the weights of the estimated S&P GSCI for 2017 (final rebalance pending publication, see footnote on previous page). Remarkably, the beta portfolio is significantly more balanced and diversified across the 24 commodities. The largest single weight is measured at 7.88% (gasoline), while the largest weight in the S&P GSCI is estimated at 22.8% (WTI crude oil – highest bar in Figure 19).

The implications are critical: the S&P GSCI is often used as a proxy for the commodity market, but the above analysis shows that it is an imperfect proxy. The market portfolio, constructed with the above methodology, is by definition statistically fully diversified and void of idiosyncratic risk, such that the variance of the market portfolio is explained by systemic risk exposures only. In pure alpha strategies for example, in which investors short the market portfolio, using the S&P GSCI *in lieu* of the market portfolio fails to perfectly isolate systemic risk. Beta return is imperfectly neutralized, and alpha returns are equally eliminated.

Comparing the beta portfolio to the benchmark

We compute the (ex-post) beta portfolio based on the first component and the above-derived weights. We examine the performance of this portfolio relative to both the S&P GSCI ER index and an equally weighted synthetic index made of the 24 commodities - (the average portfolio). Figure 20 plots the performance of beta portfolio over time and shows that an investor would have secured a better risk-return profile compared to the S&P GSCI or the average portfolio.

Figure 20 – Simple (top) and relative (bottom) cumulative performance of the beta portfolio versus the average return and the S&P GSCI portfolio



Note: Arithmetic weekly returns (not compounded)
Source: SG Cross Asset Research/Commodities

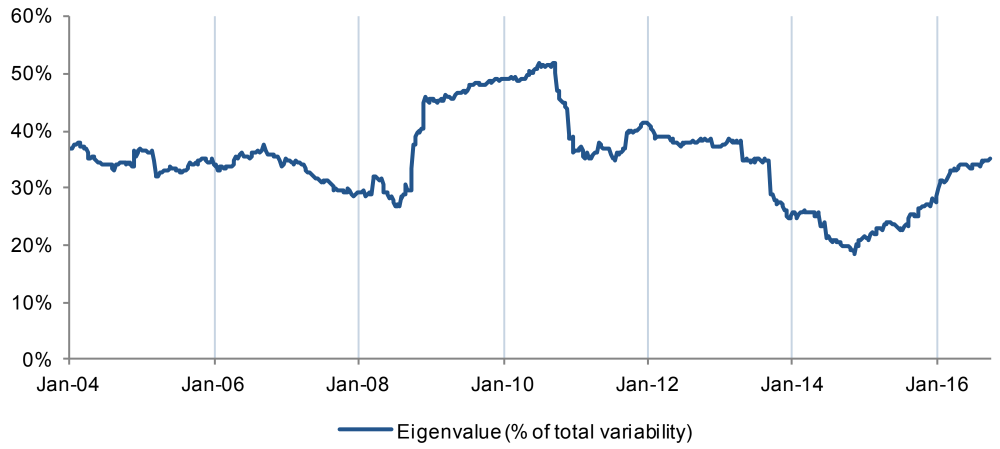
Analytically, the beta portfolio returned a 4.94% annualized return over the period 2002-2016, compared with 3.36% for the average portfolio and 0.27% for the S&P GSCI. Furthermore, the beta portfolio delivered a better Sharpe ratio (0.035) than both the average (0.00297) and the S&P GSCI (0.0016). Week-on-week returns varied within the [-15.68% ~ +13.03%] range, an improvement on the S&P GSCI min-max range of [-19.05% ~ 12.90%] and comparable in range width to the average portfolio return min-max range of [-13.28 ~ 9.53%]. Maximum drawdown is measured at 66.09% for the beta portfolio, an improvement on the S&P GSCI (83%) but weaker than the average portfolio (53%).

Dynamic PCA

The above analysis was based on a single PCA decomposition, using the full sample as input to the PCA. As such, we assumed that the drivers of systemic risk were held constant over time – this is unlikely to be the case in practice. For example, the energy complex has been a significant driver of market volatility in the last two years. In this subsection, we run PCA recursively (i.e. on a rolling basis) once a week using a trailing two-year rolling window of prices as input to the PCA. **A two-year rolling period controls for the temporary seasonal and extraordinary imbalances expected in commodities**. This procedure allows us to capture the changes of the first component – the market factor – over time.

Figure 21 depicts the changes in the level of the market risk (beta) as a percentage of total variability.

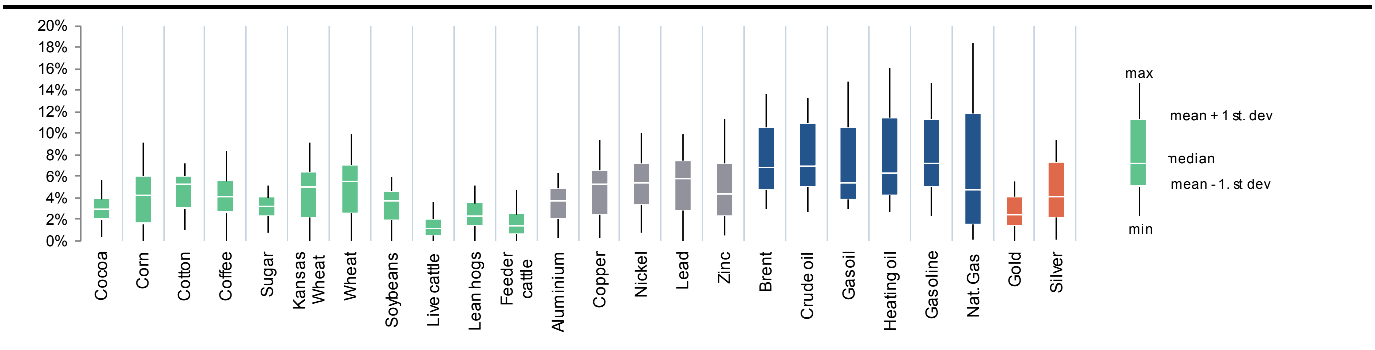
Figure 21 – The evolution of the market factor over time



The eigenvalue of the first component measures systemic risk. Expressed as a % of total risk, we can evaluate the market factor over time. We observe that systemic risk increased sharply in September 2008.
Source: SG Cross Asset Research/Commodities

Finally, we can inspect the contributions to the market risk by looking at the evolution of the squared loadings over time (**Figure 22**). In line with the results from the static PCA, we observe that the metals and energy complex have, on average, a larger weight than the grains and livestock sectors. However, we also observe that these same commodities have at times contributed significantly less to market risk. Natural gas is a striking example: it contributed on average less than 5% to market risk, but peaked at least once above 20%. Its distribution is wide, with a 10 percentage point one standard deviation range.

Figure 22– range of contributions to commodity market risk (beta) (squared loading as % eigenvalue)

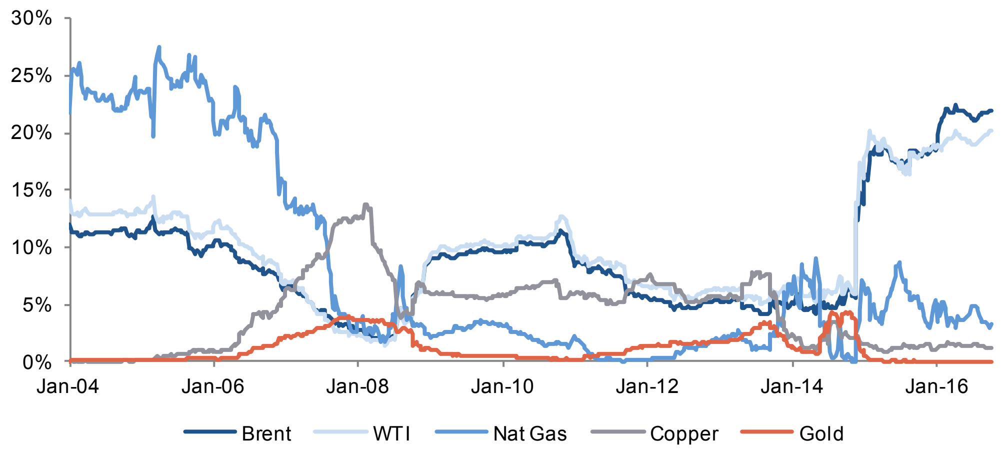


Source: SG Cross Asset Research/Commodities

Gold is noticeably different – it is never a substantial contributor to market volatility. Furthermore, we note that certain commodities exhibit more stability than others – the weightings of corn and wheat products in the first principal component are noticeably more volatile than other grains and livestock products. Silver is likewise significantly less stable than gold. This means that silver's contribution to market risk (beta) is more significant and also more variable over time.

Figure 23 plots the contribution to market risk for certain key commodities (Brent, WTI, gold, copper and natural gas). As above, we see that Natural Gas has historically shown high level of variability, while gold's contribution to systemic risk is more muted. From 2014 onwards, the crude oil subsector has been a notable driver of market risk.

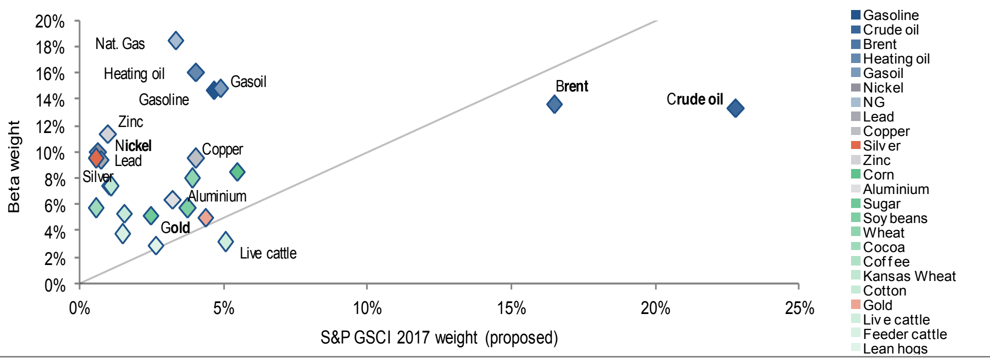
Figure 23 – Contributions to commodity market risk for selected commodities (% of beta portfolio variance)



Source: SG Cross Asset Research/Commodities

Figure 24 compares the S&P GSCI 2017 proposed weights with the maximum weight attributed to a commodity at any given time in the beta portfolio. We also plot the 45 degree diagonal line. This allows us to look at extreme positioning in the beta portfolio (relevant in times of market turbulences). What we see is that Brent and WTI are over-weighted in the S&P GSCI index compared to the beta portfolio. Gold (which is almost exactly on the diagonal line) on the other hand is approximately equally represented in both the S&P GSCI index and the beta portfolio. The base metals – particularly zinc, lead and nickel – which are only weakly represented in the S&P GSCI index can at times enter significantly the beta portfolio. For example, the S&P GSCI allocates less than 1% to Nickel, when it has historically weighed up to 10% in the beta portfolio.

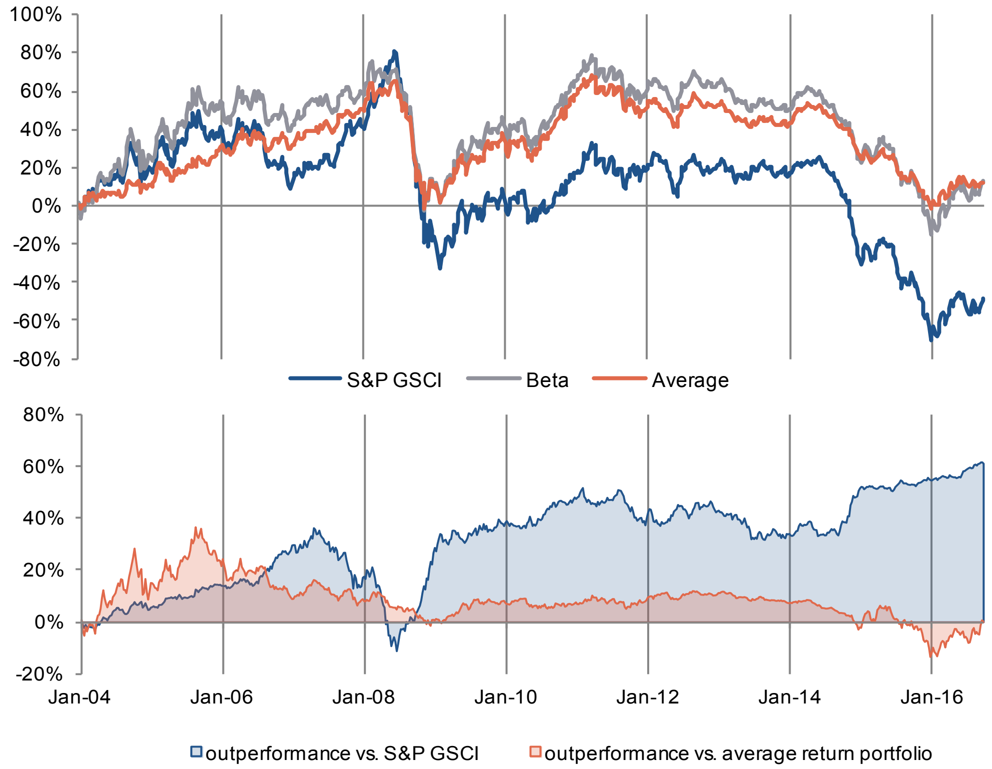
Figure 24 – comparing S&P GSCI weights with maximum beta weights (selected commodities)



Source: SG Cross Asset Research

As a final exercise, we examine the performance of the dynamic beta portfolio over time, and compare it to the S&P GSCI index as well as the average portfolio. While we do not take into account transaction costs, we compute this week's beta portfolio return using last week's PCA results – effectively rendering the portfolio tradable. **Figure 25** plots the cumulative performance of this beta portfolio. We observe that it performs similarly to the average return portfolio, and both generally outperform the S&P GSCI. We note that the beta portfolio temporarily underperforms the S&P GSCI in the wake of the GFC - but we find this intuitive: the price collapse witnessed during the GFC was widespread, and a beta portfolio is likely to reflect the systemic nature of such movements.

Figure 25 – Performance of the dynamic beta portfolio vs. S&P GSCI and average return portfolio



Source: SG Cross Asset Research/Commodities

Finally, looking at the composition of the beta portfolio on a historical basis shows the extent to which the market portfolio is time-varying, and that significant inter-sector shifts do occur (**Figure 26**).

Figure 26a - Beta portfolio weights (Jan 2008)

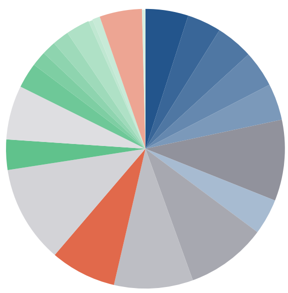


Figure 26b - Beta portfolio weights (Jan 2012)

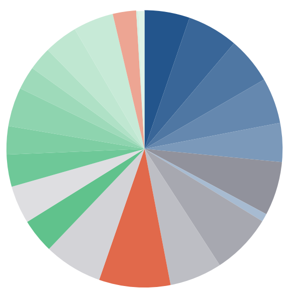
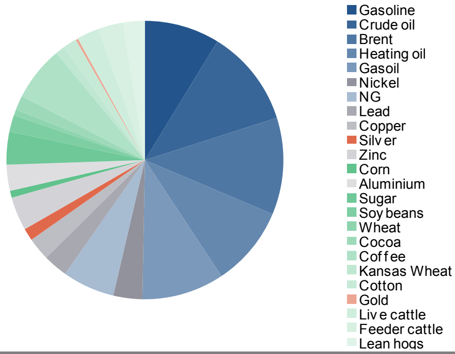


Figure 26c - Beta portfolio weights (Jan 2016)



Source: SG Cross Asset Research/Commodities

Summary of the analysis and how to take it forward

This methodology has allowed us to define and isolate the “commodity market” risk and return profile, colloquially coined “the market beta” – an abstract yet central element in tactical asset allocation. Our methodology shows that benchmark commodity indices (S&P GSCI and BCOM) are a convenient but flawed proxy for isolating the “commodity market” risk and return profile or systemic market return.

The implications for this are important: for example, in strategies that use the S&P GSCI as the short leg in long/short strategies, the market (beta) return is imperfectly neutralized, and alpha returns are equally eliminated.

In defining the “commodity market”, we showed that the commodity exposures have been significantly more diversified than in the benchmark commodity indices. We replicated the “commodity market” via our beta portfolio and found that its performance had been similar to an equally weighted commodity portfolio and that it had also outperformed the S&P GSCI (Figure 25). Moreover, a dynamic beta portfolio estimated recursively using weekly PCA signals can provide an adaptive and dynamic exposure to the commodities market – the beta – reflective of structural changes in the market.

Taking it forward

For investors looking for a more “accurate” market or beta exposure to the commodity asset class, or for investors looking to increase the efficacy of long/short (alpha / risk premia) strategy, our beta portfolio offers an effective alternative solution.

In practise, this could mean the following: for an investor looking for a more robust beta exposure to the commodity market, investing in the beta portfolio via a custom index, dynamically weighted by the PCA signals, would provide this. This approach would also reduce the excess risk caused by the weighting differentials in benchmark indices (driven by their specific construction and rules methodologies) relative to the beta portfolio (reflective of changes in the actual commodity market risk factor). For example, WTI which is down 2.8% YTD has a significantly greater weight in the S&P GSCI than it has on average had in the beta portfolio. Zinc, which is up 50.7% YTD, has a significantly smaller weight in the S&P GSCI than it has on average had in the beta portfolio. Whilst in this example it would have translated into significant outperformance of the beta portfolio relative to the S&P GSCI, it is the impact of these weight differentials between the benchmark’s weighting methodology and the weightings reflective of the actual market, as defined by our approach, which is important.

In addition, in a long/short strategy, where the long leg might be a fundamental or momentum driven strategy and the short leg a benchmark index, the short leg could be replaced by our PCA driven beta portfolio. This would more effectively neutralise market risk and reduce the risk of dampening alpha on the long leg via any inadvertent risk clustering.

Contents

Commodity Compass – previous publications

Dates	Title
Oct 2016	UPDATE – Replacing the NFCI with Bloomberg FCIs in our Commodity FCI Model
Oct 2016	Measuring “dry powder” in commodities – some alternative insights into positioning
Sep 2016	The VIX and the VVIX – tools for extreme commodity risk management
Aug 2016	Financial Conditions Indices (FCI) and long/short commodity trading signals
July 2016	Trading Economic Policy Uncertainty (EPU) with commodities
June 2016	Using Big Data to trade oil
May 2016	The impact of rate hike probabilities on gold and other commodities
April 2016	Forecasting production costs – incorporating FX, CPI and oil forecasts into the SG PCM
March 2016	Introducing the SG Production Cost Model – tracking Cost Drivers in real time
February 2016	“The Chinese Driving Season” - No monkey business
January 2016	La Niña - The likelihood of it following El Niño and how to trade it
December 2015	Commodity trading opportunities from freight markets
November 2015	The impact of hedging patterns on volatility in crude oil and natural gas
October 2015	The role of ETPs (ETFs & ETNs) in commodity price formation
September 2015	Identifying “oversold” commodities – the intersection of two extremes
August 2015	The London Metal Exchange COT report – surprisingly a very useful trading tool
July 2015	‘Rockets and feathers’ – a phenomenon for managing price retracements
June 2015	Planes, trains, automobiles (and ships) – part 2. The Baltic Petroleum Trading Model
May 2015	Planes, trains, automobiles (and ships) – part 1
April 2015	Devaluing EM currencies, the cost of carry and commodity spreads
March 2015	Softening cost floors – EM currency depreciation and falling oil prices
February 2015	The contango tango – the mechanics of contango and freight markets
January 2015	The circularity of oil prices and oil burden
December 2014	Commodity Put/Call Ratios – Enhancing trading and investment strategies
November 2014	Supply and demand – key drivers of returns this year, as nearly all of our SD models
October 2014	Interest rate increases and the influence on the commodity forward curve
September 2014	Our new Oil Product Demand Indicator (OPDI) - evidence of China’s shifting economy?
August 2014	The seasonality of commodity index investment flows
July 2014	Evaluating the magnitude and duration of risk premia during geopolitical tensions
June 2014	A new India – Copper consumption to double & gold imports to double?
May 2014	The econometrics of El Niño & the impact of ECB policy changes on commodity markets
April 2014	From Cocoa to Zinc – El Niño’s impact on commodities and whether it can be captured?
March 2014	Eight important commodity factors to watch...
February 2014	Putting recent macro events in context & analysing their impact on commodities
January 2014	2013 A bad year for price performance; but a good year for the asset class

1) SG trade recommendations (selected)

Commodity	Type	Recommendation
WTI	Flat price	**Buy Dec-17 WTI on dips** The oil markets are no longer severely oversupplied as was the case during 2Q14 – 1Q16. The supply surplus is now quite small. The next transition, from a small supply surplus to a moderate global supply deficit in 2017 would require an OPEC output cut of about 0.5 Mb/d which seems likely. We have lowered our 2016 global demand forecast to 1.24 Mb/d and forecast 2017 demand growth of 1.28 Mb/d driven by growth in India and China and other emerging markets. Driven by falling shale oil output, the US continues to lead non-OPEC supply as a whole. US output of crude (only) is projected to contract by 0.59 Mb/d in 2016, but to decline by a more moderate 0.17 Mb/d in 2017. We expect shale supply to bottom out in 2Q17 and then start growing slowly. The recent weakening of global demand growth and higher than expected output from some non-OPEC countries has put downward pressure on oil prices. We would consider significant near-term price declines a buying opportunity as OPEC is likely to announce cuts at the OPEC meeting at the end of November which should put a floor under prices. We recommend going long Dec-17 WTI (or Brent) on dips towards $50 as we expect the Dec-17 WTI price to trade up close to $60 next year.
US natural gas	Flat price	**Long Mar-17 US natural gas** Once the US natural gas injection season comes to a close, which traditionally happens early in November, there should be a market "reset". The reset will then allow for the underlying fundamental tightening that is at play to once again take control of the narrative. The storage surplus is expected to be entirely erased in early winter 16/17. A no- to slow-growth production start to 2017, as per our base-case expectation, will expose the market to more tightening through winter 16/17. Winter 16/17, under a normal weather scenario, is expected to have the second highest withdrawal (2.3-2.4tcf) since the rise of shale; second only to the Polar Vortex supported winter 13/14 (3.0tcf). Demand support will come from a combination of stronger exports (LNG and Mexico exports are already trending stronger year-on-year), industrial and R/C loads. Therefore, we recommend going long the Mar-17 US natural gas contract on dips with a price target of at least $3.50.
Aluminium, zinc	Relative value	**Short Dec-16 LME aluminium versus long Dec-16 LME zinc** Given the amount of idled capacity, lack of significant production cuts and the huge inventory overhang, we expect aluminium prices to remain depressed. Despite the lack of official cash flow profitability of many smelters and the Chinese government's intension to cut Chinese smelter capacity, we are sceptical that this will be sufficient to generate a much needed supply deficit in the near term. Falling production costs have given some breathing space to those smelters under pressure from weak market conditions, alleviating the need to shutdown production. We still see the global aluminium market in surplus to the tune of 0.5Mt this year. Zinc's fundamentals should continue to improve over the medium term as the concentrate market moves into a structural deficit. As a result, and given our expected growth in global zinc consumption of 1.4% yoy, we forecast another market deficit in 2016 of 400kt – the fifth year in succession that the market has been in deficit. This should see a decline in reported inventories taking the stocks ratio to 5.2 weeks by the end of this year from 6.8 weeks at end-2015.
Copper, lead	Relative value	**Short Dec-16 LME copper versus long Dec-16 LME lead** We expect lower copper prices during the remainder of 2016 due to sluggish demand growth and persistent oversupply. Global copper consumption should grow 2.5% yoy this year, up slightly from 2015. We expect mine production growth to accelerate to 3.7% this year from 2.4% last year, as we believe growth from new mines will be bolstered by fewer supply disruptions so far this year. We estimate that the global market balance in 2016 without further production cuts is likely to be in a surplus of 300kt. We have allowed for further supply problems in our assumed 5% (or 1.2Mt) disruption allowance for 2016. The stocks ratio is seen increasing to 4.7 weeks by year-end, from 4.1 weeks at end-2015. Demand for lead should be relatively resilient given its substantial use in autos and industrial batteries. Global car sales are holding up well. Other supportive factors are the low LME lead inventory level and a broadly balanced market. Demand for lead should increase from early autumn as auto battery producers start ramping up production ahead of Northern Hemisphere peak battery demand.

Source: SG Cross Asset Research/Commodities

2) Commodity market analysis

This section provides a **backward-looking analysis over the previous month** with a focus on the main contributors to returns in the S&P, GSCI and BCOM commodity indices.

Figure 2.1 – Oct sector performance

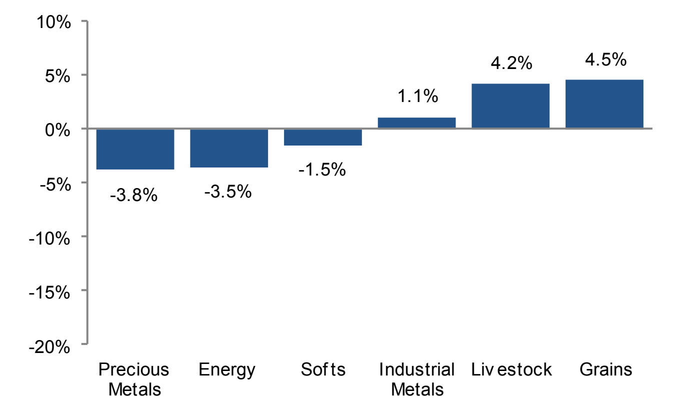


Figure 2.2 – YTD sector performance

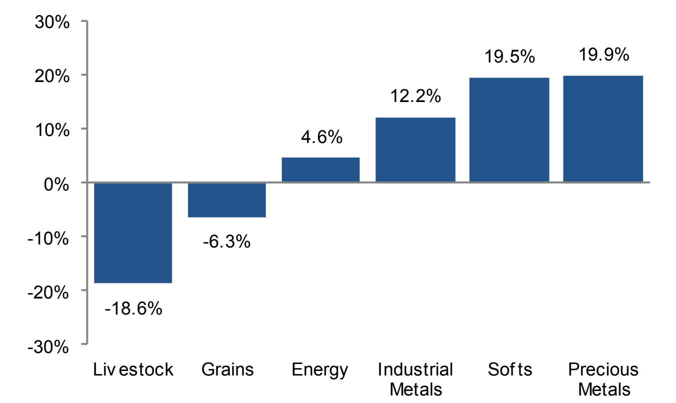


Figure 2.3 – Oct market performance

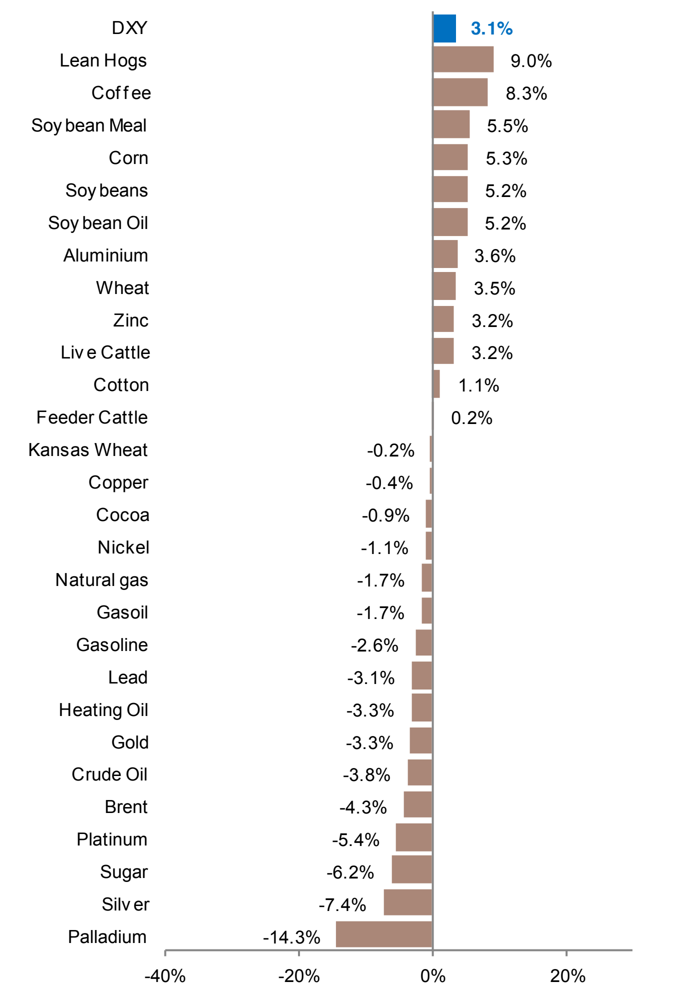
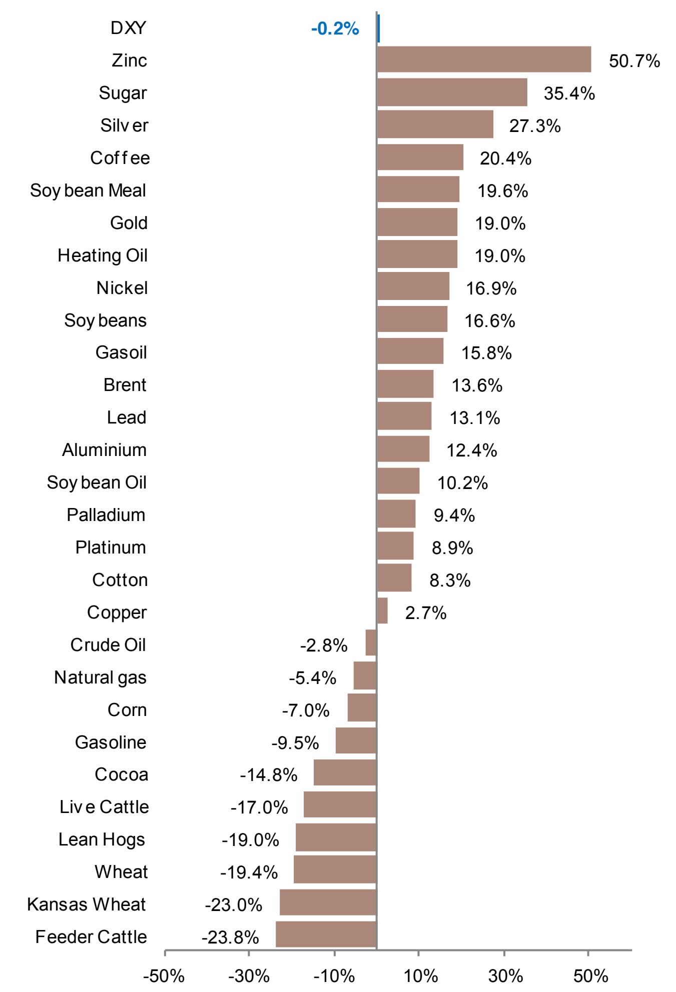


Figure 2.4 – YTD market performance



Source: SG Cross Asset Research/Commodities, Bloomberg

Energy

In October, the energy sector fell 3.5%. WTI (-3.8%) and Brent (-4.3%) were both down and the worst performing markets. Natural gas (-1.7%) was the best performing market over the month. YTD, the sector is up 4.6%, with heating oil (+19.0%) the best performing market and gasoline (-9.5%) the worst.

Petroleum prices moved generally sideways throughout October, driven by expectations that last month's OPEC decision in Algiers to target production to a range of 32.5-33Mb/d would be finalised and then implemented at the end-November OPEC meeting in Vienna. Volatility however remained elevated as the market continues to await details on the exact implementation of the deal.

Prices have rallied about 15% since the original announcement of the agreement in September. As talks between OPEC on implementation details developed in October, the general lack of consensus on production targets for individual countries and concerns about OPEC's methodology in assessing actual production levels as the basis for the calculation of production targets spurred renewed concerns whether a deal at the end-November meeting could ultimately be reached. This caused oil prices to retreat about 10% towards the end of the month. In particular, downward momentum accelerated as Iraq, the cartel's second largest producer, insisted on being excluded from the freeze due to its engagement in the war with Islamic State. This added renewed pressure on Saudi Arabia and other OPEC members to carry a higher share of the overall production cut burden. Saudi Arabia had earlier granted Iran, Iraq and Libya exemptions from the cuts in acknowledgement of their efforts to ramp up production after a prolonged period of sanctions (Iran) and internal conflicts (Nigeria, Libya and Iraq). A preliminary meeting of OPEC delegates on 28 October to resolve the many disputed issues failed to reached any meaningful conclusions.

The move higher in the dollar (DXY +3.12%), driven mainly by the anticipation of a Fed rate hike at the end of the year, also weighed on oil and commodity prices in general.

Fundamentals were generally bullish in October and supported prices. Total US crude inventories declined by 1.0Mb (vs. total expectations of a 6.1Mb increase) over the month. This was exceptional since refinery maintenance usually reaches its peak in October with a monthly average increase of 10.1Mb over the last ten years.

The horizontal rig count increased by 43 over the month, the fifth monthly increase in a row. The increase in the rig count was partly attributable to the natural depletion profile of existing shale wells, where ongoing drilling is required to maintain existing production. A slight increase in US production of 37kb/d in October combined with EIA reports of a 0.6% increase in August however, spurred some concerns about a recent rebound of US shale production and weighed on prices.

Natural gas was driven lower in October, as forecasts of higher-than-average temperatures over most of the month tempered prospects of gas-fuelled heating demand. Storage at record levels, 1.3% higher YoY and 4.9% above the five-year average though narrowing over recent months, also weighed on prices.

Industrial Metals

The industrial metals sector was up 1.1% in October. Aluminium (+3.6%) was the best performing market and lead (-3.1%) the worst. The sector is up 12.2%, YTD, with zinc (+50.7%) the best performing commodity and copper (+2.7%) the worst.

Industrial metals were driven by an improvement in fundaments across the complex, combined with the strength in energy prices and key producer currencies (USDCLP -0.93%) acting to support prices and offset the negative impact of the move higher in the dollar (DXY +3.12%). Rising producer currencies and energy prices increase implied production cost floors and raise the risk for supply cuts.

Aluminium prices were driven higher as a 13.1% price rally at the Shanghai Futures Exchange improved market sentiment and offset some of the negative impact of the dollar. The surge in Shanghai prices was mainly attributed to supply shortages in the Chinese market due to transport bottlenecks and the increase in coal prices, driving up production costs and hindering output. An increase in LME and Shanghai stocks of 16,900mt and 1,939mt however, limited upward price movements.

Copper (0.0%) was flat in October on a combination of mixed factors. Poor export data and reports of a 25% YoY decline of refined copper imports from China in September were bearish for prices. Expectations of a lower copper surplus for this year with Freeport, the world's largest listed copper miner, lowering its output forecast from 5bn lbs to 4.8bn lbs, and decreases in LME and Shanghai inventories of 51,400mt and 4,510mt supported prices. COMEX stocks however increased by 1,386 short tons.

Lead decreased in October as the move higher in the dollar and inventory increases weighed on prices. Shanghai inventories increased by 6,271mt, partly offset by a 1,750mt decrease in LME stocks.

Zinc (+3.2%) prices gained in October as reports of a mine-shut-down in Australia by Glencore and environmental crack-down in China strengthened expectations of a supply deficit this year amid tightness in concentrate availability. Increases in LME and Shanghai inventories of 11,450mt and 5,350mt however, limited the upward.

Nickel (-1.1%) decreased following the move higher in the dollar and reports of China's largest stainless steel producer cutting production by 200kt in November. This spurred new concern about potentially lower demand since two thirds of the nickel output is used for stainless steel production. LME inventories increased by 1,764mt and Shanghai stocks decreased by 2,858mt over the month.

Precious Metals

The precious metals sector was down 3.8% and the worst performing sector in October, with gold (-3.3%) and silver (-7.4%) both decreasing. YTD, the sector is up 19.9%, with gold (+19.0%) and silver (+27.3%) both up significantly. Precious metals is the best performing sector YTD.

Gold prices fell in October following the move higher in the dollar and the release of strong US economic data strengthening the case for a Fed rate hike by the end of the year. The widening lead of Clinton over Trump in polls over the month however, eased some policy uncertainty surrounding the forthcoming US elections, tempering safe-haven demand for gold. The outflow of 569,000 ounces from ETF holdings on 21 October, the biggest one-day decrease since July 2013, caused some concerns about the stability of the ongoing inflows, but with prices largely unresponsive, this was mainly seen as a one-off event. Overall ETF holdings increased 0.43% in October - the ninth monthly increase this year.

Agriculture

The grains sector (corn, wheat, Kansas wheat and soybeans) was up 4.5% in October and the best performing sector. Corn (+5.3%) was the best performing market and Kansas wheat (-0.2%) the worst. The softs sector (cotton, coffee, sugar and cocoa) fell 1.5% in October. Coffee (+8.3%) was the best performing market and sugar (-6.2%) the worst. YTD, the grains sector is down 6.3% and the softs sector up 19.5%.

Corn prices rallied in October following USDA forecasts of lower yields resulting in diminished supplies for 2016/17 and increased exports, partly driven by the appreciation of the BRL making US corn more competitive.

Wheat (+3.5%) prices moved higher following increased in demand from Egypt, the world's largest importer, which rose to a two-year high. A prolonged period of dryness in the US, the world's second largest exporter, spurred concerns about the crop outlook and also supported prices.

Soybeans (+5.2%) increased on strong demand from China and dry weather in the Latam region, shrugging of a widely bearish USDA report which showed yields at record levels and an increase in supplies from last month.

Coffee prices continued their rally in October as dry weather conditions in Brazil and the appreciation of the BRL, which reduced returns by elevating production costs, combined acted to temper output and boost prices. Global inventories of producing countries at their lowest levels in five years were also supportive for prices.

Sugar fell in October as this year's sharp price rally lost steam following reports of increased output from Brazil, the world's largest producer.

Cotton (+1.1%) was driven higher on USDA forecasts of higher demand from China, Bangladesh and India amid falling world inventories in 2016/17.

Cocoa (-0.9%) fell on expectations of a good harvest for the season 2016-17 in the Ivory Coast, the world's largest producer, after adverse weather conditions from previous months eased and improved the crop outlook.

Livestock

The livestock sector was up 4.2% in October. Lean hogs was the best performing market (+9.0%) and feeder cattle (+0.2%) the worst. YTD, the sector is down 18.6%. Livestock is the worst performing sector YTD.

Lean hogs rallied in October driven by USDA reports of increased exports amid strong demand from China, the world's biggest pork consumer. Live cattle (+3.2%) prices increased following reports by the USDA of lower than expected cattle in feedlots in September.

Sources include but are not restricted to: SG Cross Asset Research/Commodities, Bloomberg, The Financial Times, The Wall Street Journal, Reuters, Agrimoney.com and AgWeb.com.

2a) Forward curves – spread levels across the curve

The top row of each square in Figure 2.5 defines the spread in terms of the month (M) and expiry year (Y) in the form ((MY)x/(MY)x+1), where x represents each successively listed contract. The second row shows the absolute level of the spread at month-end, calculated as (price (MY)x – price (MY)x+1).

Figure 2.5 – Spread levels across the forward curve. Backwardation and contango shown in green and red respectively

Futures contracts

	1/2	2/3	3/4	4/5	5/6	6/7	7/8	8/9	9/10	10/11	11/12	12/13	13/14	14/15	15/16	16/17	17/18	18/19	19/20	20/21	21/22	22/23	23/24
Crude Oil (CL)	Z6/F7 -0.60	F7/G7 -0.59	G7/H7 -0.57	H7/J7 -0.51	J7/K7 -0.42	K7/M7 -0.34	M7/N7 -0.27	N7/Q7 -0.23	Q7/U7 -0.20	U7/V7 -0.18	V7/X7 -0.19	X7/Z7 -0.20	Z7/F8 -0.13	F8/G8 -0.13	G8/H8 -0.12	H8/J8 -0.13	J8/K8 -0.14	K8/M8 -0.15	M8/N8 -0.11	N8/Q8 -0.12	Q8/U8 -0.13	U8/V8 -0.14	V8/X8 -0.15
Brent (CO)	Z6/F7 -0.31	F7/G7 -0.69	G7/H7 -0.62	H7/J7 -0.55	J7/K7 -0.47	K7/M7 -0.39	M7/N7 -0.34	N7/Q7 -0.28	Q7/U7 -0.24	U7/V7 -0.23	V7/X7 -0.24	X7/Z7 -0.20	Z7/F8 -0.20	F8/G8 -0.21	G8/H8 -0.21	H8/J8 -0.21	J8/K8 -0.20	K8/M8 -0.19	M8/N8 -0.20	N8/Q8 -0.17	Q8/U8 -0.16	U8/V8 -0.15	V8/X8 -0.13
Gasoline (XB)	X6/Z6 3.00	Z6/F7 0.23	F7/G7 -1.37	G7/H7 -2.36	H7/J7 -18.38	J7/K7 -1.37	K7/M7 0.06	M7/N7 0.89	N7/Q7 1.76	Q7/U7 2.59	U7/V7 12.03	V7/X7 2.61	X7/Z7 1.24	Z7/F8 -0.21	F8/G8 -1.52	G8/H8 -2.29	H8/J8 -19.88	J8/K8 -0.98	K8/M8 0.09	M8/N8 1.28	N8/Q8 1.78	Q8/U8 2.58	U8/V8 13.35
Heating Oil (HO)	X6/Z6 -0.84	Z6/F7 -1.77	F7/G7 -1.54	G7/H7 -0.79	H7/J7 -0.04	J7/K7 -0.43	K7/M7 -0.51	M7/N7 -0.92	N7/Q7 -1.12	Q7/U7 -1.21	U7/V7 -1.14	V7/X7 -1.06	X7/Z7 -1.00	Z7/F8 -1.05	F8/G8 -0.50	G8/H8 -0.05	H8/J8 0.45	J8/K8 0.00	K8/M8 -0.30	M8/N8 -0.80	N8/Q8 -1.00	Q8/U8 -1.05	U8/V8 -1.00
Gasoil (QS)	X6/Z6 -1.00	Z6/F7 -3.25	F7/G7 -4.00	G7/H7 -3.50	H7/J7 -3.00	J7/K7 -2.75	K7/M7 -2.50	M7/N7 -3.25	N7/Q7 -3.00	Q7/U7 -3.00	U7/V7 -3.00	V7/X7 -1.75	X7/Z7 -1.25	Z7/F8 -2.75	F8/G8 -2.75	G8/H8 -2.75	H8/J8 -2.00	J8/K8 -2.00	K8/M8 -1.75	M8/N8 -3.00	N8/Q8 -3.00	Q8/U8 -2.50	U8/V8 -2.50
Natural gas (NG)	Z6/F7 -0.17	F7/G7 -0.03	G7/H7 0.02	H7/J7 0.13	J7/K7 0.01	K7/M7 -0.03	M7/N7 -0.03	N7/Q7 0.00	Q7/U7 0.02	U7/V7 -0.02	V7/X7 -0.04	X7/Z7 -0.15	Z7/F8 -0.09	F8/G8 0.03	G8/18 0.07	18/18 0.42	18/18 0.03	18/18 -0.02	18/18 -0.02	18/18 0.00	18/18 0.01	18/18 -0.03	18/18 -0.05
Copper (LP)	X6/Z6 -4.75	Z6/F7 -3.50	F7/G7 -4.00	G7/H7 -3.75	H7/J7 -3.00	J7/K7 -3.00	K7/M7 -3.25	M7/N7 -3.25	N7/Q7 -3.25	Q7/U7 -3.25	U7/V7 -3.25	V7/17 -3.25	17/17 -3.25	17/18 -2.75	18/18 -2.75	18/18 -2.75	18/18 -2.75	18/18 -2.75	18/18 -2.75	18/18 -2.75	18/18 -2.75	18/18 -2.50	18/18 -2.50
Aluminium (LA)	X6/Z6 0.50	Z6/F7 -1.75	F7/G7 0.25	G7/H7 -1.50	H7/J7 -2.75	J7/K7 -2.25	K7/M7 -4.50	M7/N7 -2.50	N7/Q7 -3.25	Q7/U7 -4.25	U7/V7 -3.00	V7/17 -2.75	17/17 -3.25	17/18 -3.75	18/18 -4.25	18/18 -3.50	18/18 -3.75	18/18 -3.75	18/18 -4.50	18/18 -3.75	18/18 -3.75	18/18 -4.50	18/18 -3.75
Zinc (LX)	X6/Z6 -5.00	Z6/F7 -3.50	F7/G7 0.00	G7/H7 -3.00	H7/J7 -1.75	J7/K7 -2.25	K7/M7 -0.75	M7/N7 0.00	N7/Q7 1.25	Q7/U7 1.25	U7/V7 1.25	V7/X7 1.25	X7/Z7 1.25	Z7/F8 5.00	F8/G8 5.00	G8/H8 5.00	H8/J8 5.00	J8/K8 5.00	K8/M8 5.00	M8/N8 3.50	N8/Q8 3.50	Q8/U8 3.25	U8/V8 3.25
Nickel (LN)	X6/Z6 -17.50	Z6/F7 -15.00	F7/G7 -13.50	G7/H7 -13.50	H7/J7 -17.00	J7/K7 -13.00	K7/M7 -17.50	M7/N7 -11.00	N7/Q7 -11.00	Q7/U7 -11.00	U7/V7 -11.00	V7/X7 -11.00	X7/Z7 -11.00	Z7/F8 -10.00	F8/G8 -10.00	G8/H8 -10.00	H8/J8 -10.00	J8/K8 -10.00	K8/M8 -10.00	M8/N8 -10.00	N8/Q8 -10.00	Q8/U8 -10.00	U8/V8 -10.00
Lead (LL)	X6/Z6 -4.00	Z6/F7 -4.00	F7/G7 -3.75	G7/H7 -4.25	H7/J7 -3.00	J7/K7 -2.75	K7/M7 -2.25	M7/N7 -2.25	N7/Q7 -2.25	Q7/U7 -1.25	U7/V7 -1.25	V7/X7 -1.00	X7/Z7 -1.00	Z7/F8 -1.50	F8/G8 -1.50	G8/H8 -1.50	H8/J8 -1.50	J8/K8 -1.50	K8/M8 -1.50	M8/N8 -1.50	N8/Q8 -1.50	Q8/U8 -1.25	U8/V8 -1.25
Gold (GC)	X6/Z6 -1.60	Z6/F7 -2.00	F7/G7 -1.80	G7/J7 -3.40	J7/M7 -3.10	M7/Q7 -2.90	Q7/V7 -2.80	V7/Z7 -2.80	Z7/G8 -2.80	G8/J8 -2.50	J8/M8 -2.50	M8/Q8 -3.20	Q8/Z8 -3.60	Z8/M9 -6.30	M9/Z9 -6.50	Z9/M0 -6.50	M0/Z0 -7.90						
Silver (SI)	X6/Z6 -0.03	Z6/F7 -0.04	F7/H7 -0.08	H7/K7 -0.06	K7/N7 -0.06	N7/U7 -0.06	U7/Z7 -0.08	Z7/F8 -0.03	F8/H8 -0.05	H8/K8 -0.03	K8/N8 -0.03	N8/U8 -0.05	U8/Z8 -0.05	Z8/N9 -0.13									
Corn (C)	Z6/H7 -8.00	H7/K7 -6.75	K7/N7 -6.75	N7/U7 -6.25	U7/Z7 -7.25	Z7/H8 -9.25	H8/K8 -5.25	K8/N8 -3.50	N8/U8 2.75	U8/Z8 -0.50													
Wheat (W)	Z6/H7 -17.50	H7/K7 -14.50	K7/N7 -13.25	N7/U7 -14.25	U7/Z7 -16.75	Z7/H8 -11.75	H8/K8 -4.25	K8/N8 3.00	N8/U8 -6.75	U8/Z8 -15.00													
Soybeans (S)	X6/F7 -9.50	F7/H7 -6.75	H7/K7 -5.50	K7/N7 -4.50	N7/Q7 2.50	Q7/U7 17.75	U7/X7 13.75	X7/F8 -0.75	F8/H8 2.00	H8/K8 0.50													
Coffee (KC)	Z6/H7 -3.40	H7/K7 -2.15	K7/N7 -1.75	N7/U7 -1.65	U7/Z7 -2.20	Z7/H8 -1.75	H8/K8 -1.00	K8/N8 -0.95	N8/U8 -0.90	U8/Z8 -1.60													
Sugar (SB)	H7/K7 0.46	K7/N7 0.55	N7/V7 0.41	V7/H8 0.21	H8/K8 0.63	K8/N8 0.56	N8/V8 0.25	V8/H9 0.14	H9/K9 0.57	K9/N9 0.42													
Cotton (CT)	Z6/H7 -0.51	H7/K7 -0.48	K7/N7 -0.08	N7/V7 0.82	V7/Z7 -0.05	Z7/H8 -0.20	H8/K8 0.03	K8/N8 -0.15	N8/V8 -0.03	V8/Z8 -0.09													
Cocoa (CC)	Z6/H7 92.00	H7/K7 19.00	K7/N7 -1.00	N7/U7 -2.00	U7/Z7 2.00	Z7/H8 2.00	H8/K8 -5.00	K8/N8 -3.00															
Live Cattle (LC)	Z6/G7 -0.80	G7/J7 0.35	J7/M7 8.13	M7/Q7 2.48	Q7/V7 -1.20	V7/Z7 -0.90																	
Lean Hogs (LH)	Z6/G7 -6.68	G7/J7 -7.43	J7/K7 -7.88	K7/M7 -3.70	M7/N7 -0.67	N7/Q7 0.15	Q7/V7 10.65																

Please note: Each box show s the spread betw een each listed contract dow n the curve and w ill not necessarily cover every calender month.

KEY (letters refer to expiry months, numbers to expiry years)

F	G	H	J	K	M	N	Q	U	V	X	Z
Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec

Figure 2.6 – Crude oil WTI: six-month forward curve history

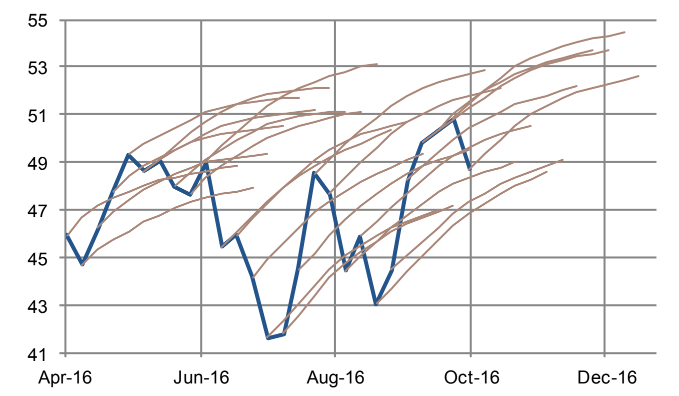
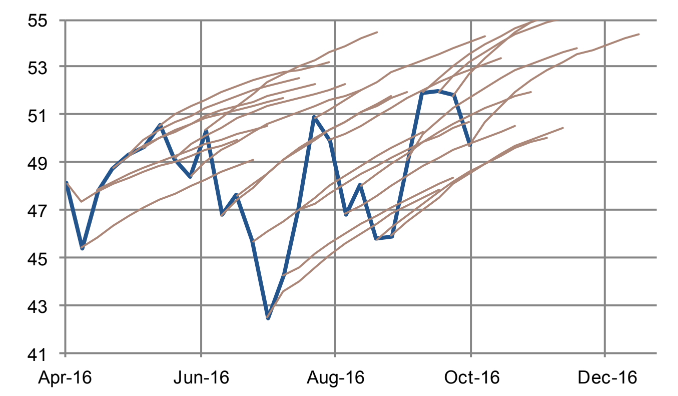


Figure 2.7 – Brent: six-month forward curve history



Source: SG Cross Asset Research/Commodities, Bloomberg

3) Principal Component Analysis (PCA)

Please see the end of this section for an explanation of PCA and the Economic Policy Uncertainty Indices (EPU)

The average level of systemic risk (macro, dollar and liquidity factors combined fell slightly in October with no clear shifts in the risk profile in any particular sector. The biggest individual changes occurred in soybeans, aluminium and coffee, which saw large decreases in systemic risk and nickel, live cattle and silver where relatively large increases in systemic risk occurred. Gold remained the commodity most sensitive to systemic risk and lean hogs the least.

The dollar factor continues to be the dominant driver of systemic risk across the asset class, which is largely consistent with the perceived drivers of macroeconomic risk currently – most notably the Fed rate hike timeline and the US election. This is a relatively unusual profile, as shown in Figure 3.6, as the macro factor is typically the main driver of systemic risk. A currency-dominated systemic risk profile has not generally been associated with the high levels of volatility often evident when the macro (risk-on/risk-off) factor is the more dominant.

Economic Policy Uncertainty (EPU) declined in the EU and China, but rose marginally in the US. In general, a reduced or declining EPU profile suggests that systemic risk, or more specifically, negatively orientated systemic risk should likely decline across the asset class.

Figure 3.1 – PCA profile for copper

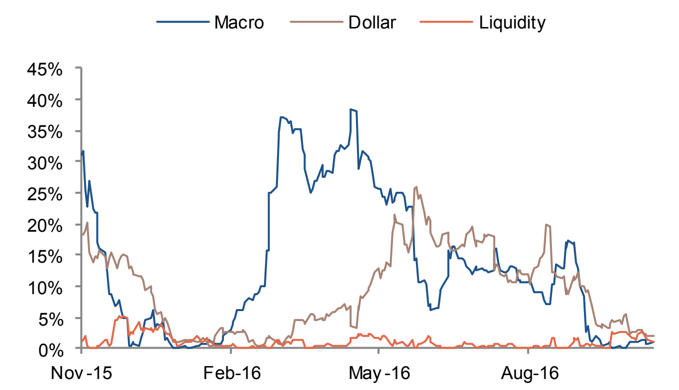


Figure 3.2 – PCA profile for Brent

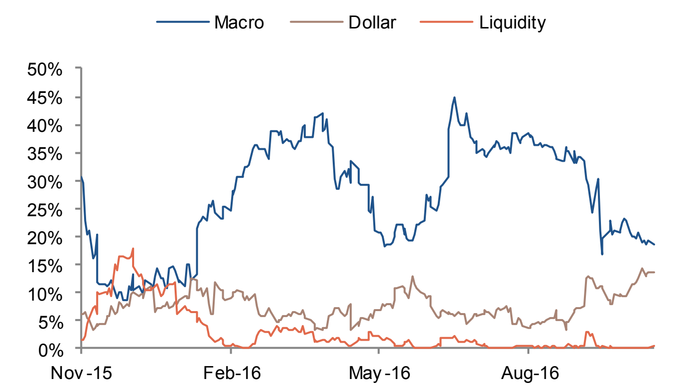


Figure 3.3 – PCA profile for gold

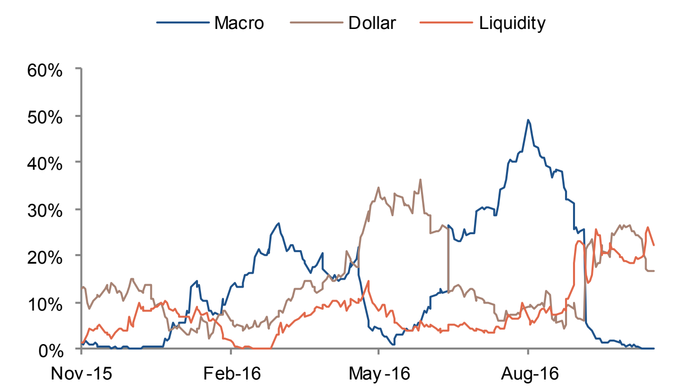
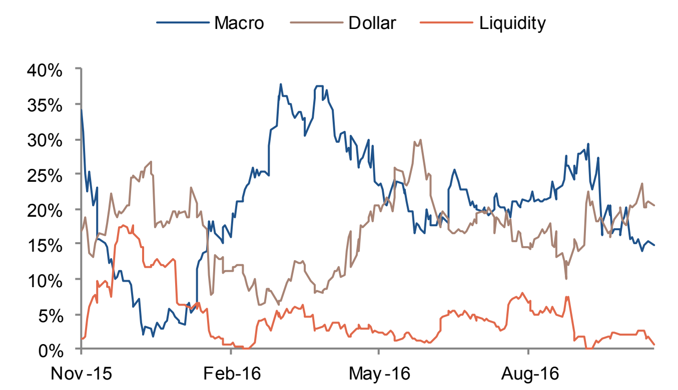


Figure 3.4 – PCA profile for the BCOM



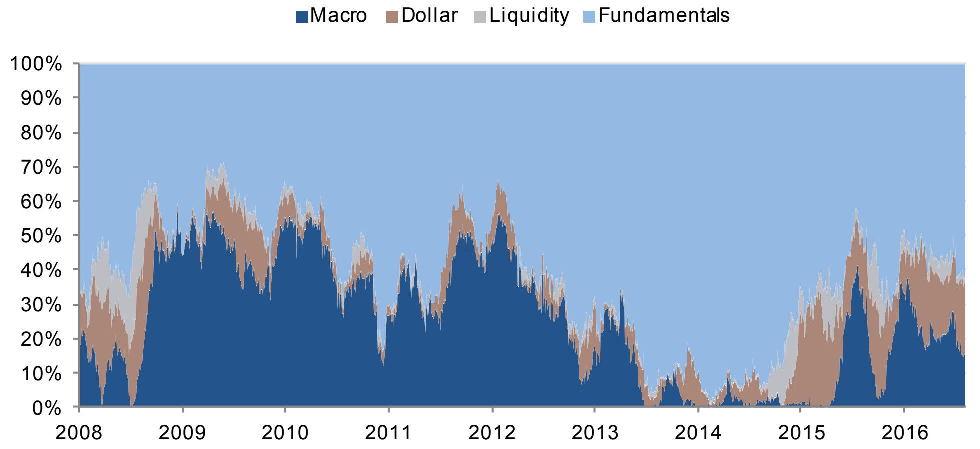
Figures 3.1 to 3.4 show the change in explanatory power of the major factors (as determined by the PCA model) over the past 12 months for copper, Brent, gold and the BCOM commodity index. The underlying prices used in the analysis are the daily settlement prices of the BCOM F3 excess return index and the daily settlement prices of the respective BCOM F3 excess return component indices for the individual markets.
Source: SG Cross Asset Research/Commodities

Figure 3.5 – PCA analysis: change in profile over the month

	October-2016				September-2016			
	Macro	Dollar	Liquidity	Fundamental	Macro	Dollar	Liquidity	Fundamental
Aluminium	0.05%	1.94%	1.73%	96.27%	2.27%	3.11%	5.65%	88.97%
Copper	0.89%	1.99%	1.08%	96.04%	0.45%	3.97%	0.16%	95.41%
Lead	0.27%	1.00%	1.73%	97.00%	0.31%	2.69%	0.03%	96.97%
Nickel	16.36%	0.12%	1.54%	81.98%	11.95%	0.00%	0.40%	87.65%
Zinc	6.03%	0.25%	2.08%	91.64%	5.75%	0.22%	0.11%	93.92%
Gold	0.08%	16.61%	22.30%	61.02%	1.46%	20.96%	20.52%	57.07%
Silver	2.18%	15.56%	16.04%	66.22%	1.67%	17.54%	11.13%	69.66%
Crude Oil (WTI)	17.82%	14.33%	0.27%	67.58%	19.02%	11.85%	0.17%	68.97%
Brent	18.66%	13.70%	0.27%	67.36%	19.46%	10.68%	0.24%	69.62%
Heating Oil	14.41%	13.57%	0.67%	71.35%	15.74%	9.27%	0.34%	74.65%
Gasoline	13.59%	9.76%	1.11%	75.53%	16.56%	10.46%	1.34%	71.64%
Gasoil	10.96%	6.49%	1.73%	80.82%	15.58%	3.96%	2.30%	78.16%
Natural Gas	0.14%	2.33%	0.90%	96.62%	0.42%	0.89%	0.05%	98.64%
Corn	0.01%	1.52%	0.01%	98.46%	1.31%	2.58%	2.34%	93.78%
Wheat	0.09%	6.14%	0.26%	93.51%	4.39%	2.70%	0.37%	92.53%
Soybeans	1.19%	0.29%	1.05%	97.48%	4.16%	1.08%	7.55%	87.21%
Cotton	0.49%	0.53%	0.76%	98.23%	4.85%	0.09%	1.02%	94.05%
Sugar	3.71%	0.29%	0.83%	95.17%	2.65%	0.40%	0.67%	96.27%
Coffee	3.46%	5.95%	1.67%	88.93%	6.16%	8.32%	2.76%	82.77%
Cocoa	5.13%	14.39%	0.25%	80.24%	11.69%	13.01%	0.03%	75.27%
Live Cattle	0.00%	3.87%	2.87%	93.26%	0.48%	0.12%	2.14%	97.27%
Lean Hogs	0.01%	1.16%	0.45%	98.38%	1.29%	0.08%	0.22%	98.41%
BCOM	**14.94%**	**20.51%**	**0.69%**	**63.87%**	**17.94%**	**18.37%**	**1.46%**	**62.24%**
AVERAGE	5.25%	5.99%	2.71%	86.05%	6.71%	5.64%	2.71%	84.95%

Figure 3.5 shows the change in explanatory power for each of the major factors across 22 major commodity markets and the BCOM commodity index over the month. The underlying prices used in the analysis are the daily settlement prices of the BCOM F3 excess return index and the daily settlement prices of the respective BCOM F3 excess return component indices for the individual markets. The average shown at the bottom of the table is the equally-weighted arithmetic mean of the 22 markets. The average value will differ from the BCOM value due to weighting and correlation effects.
Source: SG Cross Asset Research/Commodities

Figure 3.6 – Historical PCA profile of the BCOM commodity index since 2008



Source: SG Cross Asset Research/Commodities

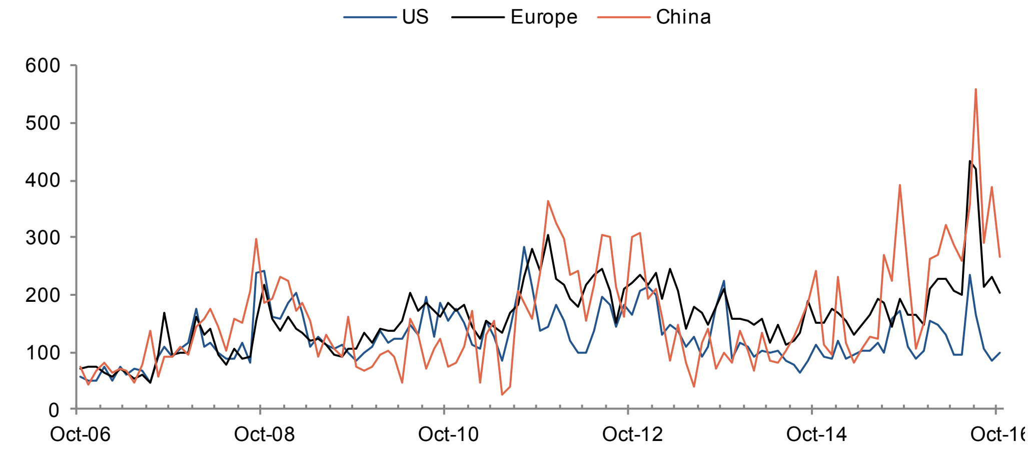
PCA explained:
Principal Component Analysis (PCA) is a statistical tool that allows us to break down commodity price returns and isolate the major explanatory variables. SG has developed a PCA model, specifically for commodity markets, that uses 23 different non-fundamental variables. These include measures of inflation, currency changes, credit spreads, implied volatility, equity and changes in equity indices. These variables are simplified into three principal components through the PCA process. Each component is a linear combination of the original 23 variables that can be mapped to a "real world" factor by examining and interpreting the underlying weightings of these variables. The first factor is defined as a macro-related factor, the second a currency factor, and the third an interest rate or liquidity factor. Each of the three factors is linearly regressed against each commodity to determine the explanatory power each factor has on the variance of that commodity. The residual, or that which is not explained by the regression process, is attributed to fundamentals (specific commodity supply & demand dynamics).

3a) Economic Policy Uncertainty (EPU) Indices

Economic Policy Uncertainty (EPU) is a class of economic risk where the future path of government policy is uncertain. Policy uncertainty may refer to uncertainty about monetary or fiscal policy, the tax or regulatory regime, or uncertainty over electoral outcomes that will influence political leadership.

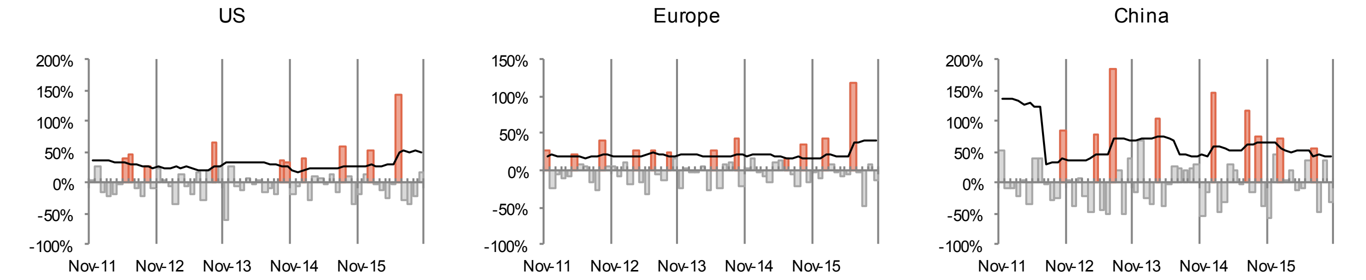
In the context of our PCA analysis (Section 3), changes in EPU can lead to changes in systemic risk. Specifically, increases in EPU are associated with negatively orientated systemic risk. In order to track these changes, we use the EPU indices, developed by Economic Policy Uncertainty[7]

Figure 3.7 – Monthly EPU indices for the US, EU and China. Increases (decreases) in the indices show rising (declining) EPU



Source: SG Cross Asset Research/Commodities

Figure 3.8 – Monthly changes in the US, EU and China EPU Index. Black line illustrates standard deviation (12m rolling) threshold. Changes in EPU in excess of this threshold are significant (red bars) and are associated with commodity price weakness



Source: SG Cross Asset Research/Commodities, Bloomberg

Economic Policy Indices:
The Baker, Bloom and Davis news-based index of economic policy uncertainty for the US is based on the frequency of newspaper references to policy uncertainty. 10 large newspapers are used.
The European Policy Index is constructed based on newspaper articles regarding policy uncertainty.
The China Index is constructed using a scaled frequency count of articles about policy-related economic uncertainty in the South China Morning Post (SCMP), Hong Kong's leading English-language newspaper. The method follows our news-based indices of economic policy uncertainty for the US and other countries.
We only consider the news-flow EPU Indices.
Source: www.policyuncertainty.com.

[7] *Baker, Scott; Bloom, Nick; Davis, Steven (2011). "Measuring Policy Uncertainty?" (PDF). Stanford Mimeo.*

4) Cost curve dynamics - the SG Production Cost Model

Changes in currencies, inflation, energy costs and metal prices can have a profound impact on mining costs. Understanding the impact of these changes is critical in assessing how individual mining costs and, by extension, broader industry cost curves are evolving. The model provides a more accurate and timely assessment of the cost curve, allowing the current level of price support and the likelihood of cuts in mine supply to be more accurately addressed. The model is described in the SG Production Cost Model (SG PCM) publication.

Figure 4.1 – Changes in the Cost Floor (90th Percentile) – Using the Spot Price (SPM) Methodology. The implied cost floor is shown in blue, the published cost floor in brown

Metal	Price	90th Percentile	Implied Cost (PCM)	Change in Cost Floor ($)	Change in Cost Floor (%)	Price - Cost Floor ($)	Price - Cost Floor (%)
SPOT PRICE METHODOLOGY							
Copper	$4,853	$3,931	**$4,038**	$107	2.73%	$815	20.19%
Zinc	$2,458	$1,548	**$1,487**	-$61	-3.93%	$971	65.30%
Lead	$2,065	$1,390	**$1,416**	$26	1.85%	$649	45.83%
Nickel	$10,475	$11,478	**$10,976**	-$502	-4.37%	-$501	-4.56%

* Total Cash Costs (SNL Metals & Mining)

Source: SG Cross Asset Research/Commodities, SNL Metals & Mining , Bloomberg

Figure 4.2 – Copper – Industry costs vs SG PCM implied costs. Implied costs derived from 199 mines (SPM)

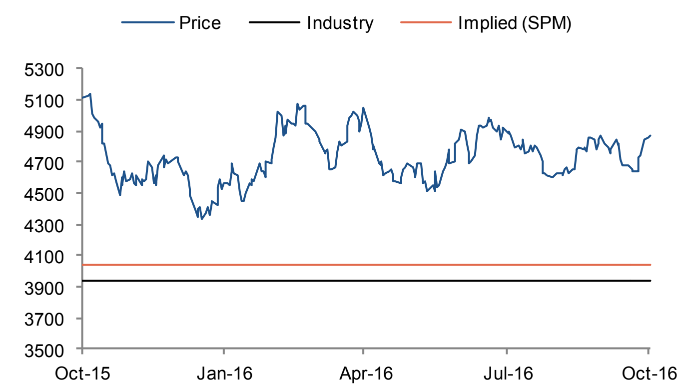


Figure 4.3 – Zinc – Industry costs vs SG PCM implied costs. Implied costs derived from 71 mines (SPM)

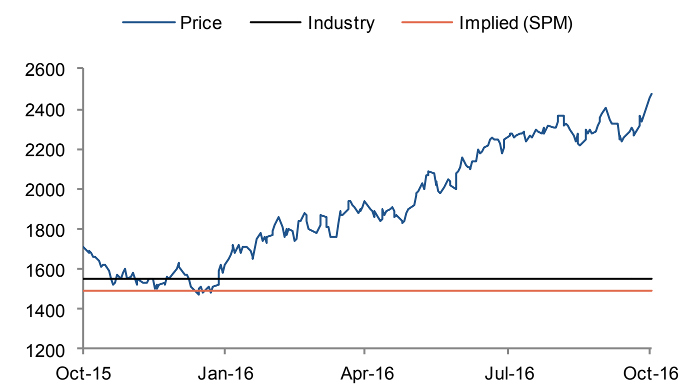


Figure 4.4 – Lead – Industry costs vs SG PCM implied costs. Implied costs derived from 56 mines (SPM)

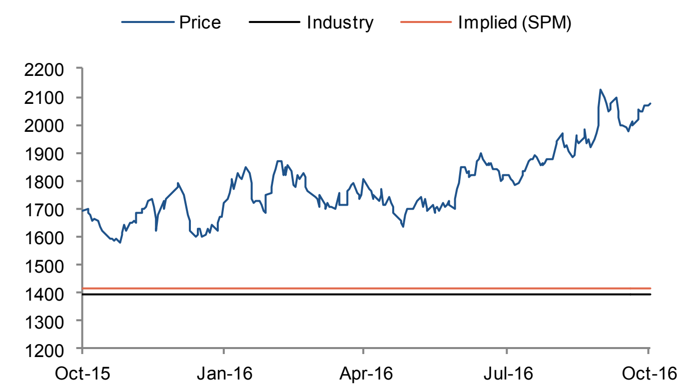
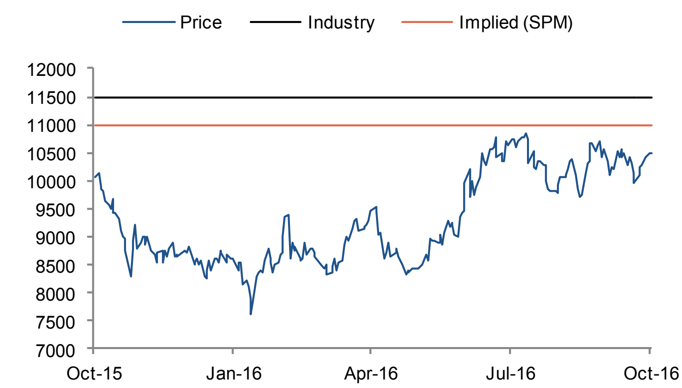


Figure 4.5 – Nickel – Industry costs vs SG PCM implied costs. Implied costs derived from 67 mines (SPM)



SPM = Spot Price Methodology, "Industry" refers to the 90th percentile total cash costs (SNL Metals & Mining)
Source: SG Cross Asset Research/Commodities, SNL Metals & Mining, Bloomberg

4a) Individual mine analysis

The following charts illustrate how the most recently reported total cash costs - defined as the sum of all minesite costs (mining + milling), transport and offsite costs, smelting and refining costs and royalties - have been impacted by changes in the underlying cost drivers (currency movements, inflation, oil (fuel) prices, treatment and refining charges and the metal prices themselves).

Each bubble represents a mine – the area of the bubble is a function of its most recently reported total annual production (scaled across all metals). The position on the x-axis is driven by the most recently reported total cash cost (sourced from SNL, Metals & Mining[8]) and the position on the y-axis is the extent by which the total cash cost has been shifted by recent changes in the Cost Drivers using our Spot Price Methodology.

Please refer to the SG Production Cost Model (SG PCM) publication for full details.

Figure 4.6 – Copper – Change in total cash costs for all mines in the top ten largest producing countries

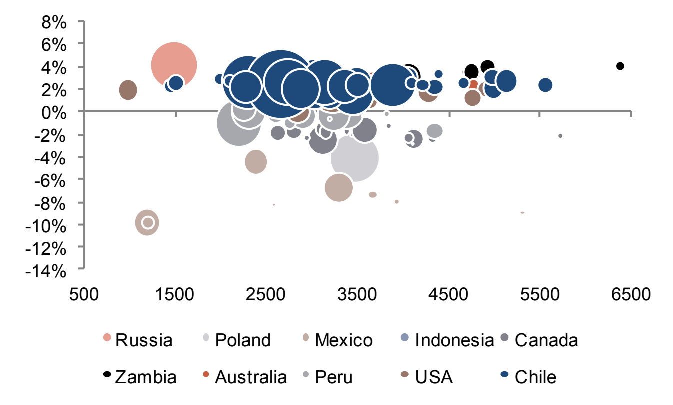


Figure 4.7 – Zinc – Change in total cash costs for all mines in the top ten largest producing countries

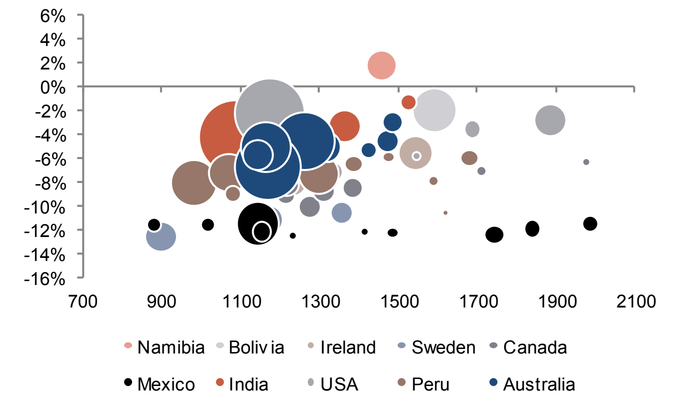


Figure 4.8 – Lead – Change in total cash costs for all mines in the top ten largest producing countries

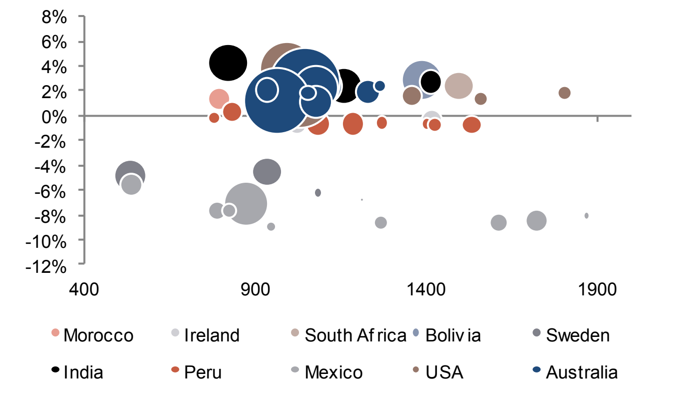
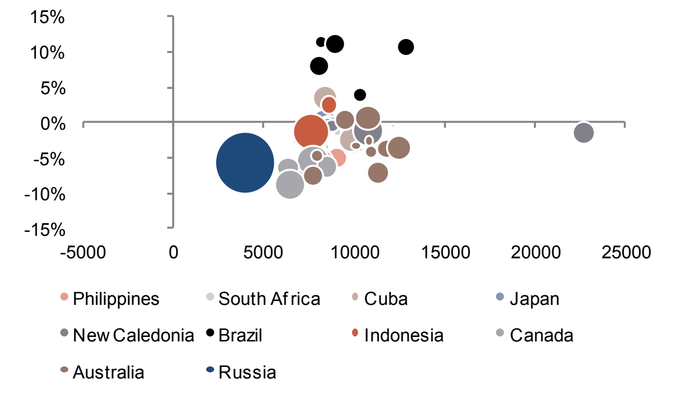


Figure 4.9 – Nickel – Change in total cash costs for all mines in the top ten largest producing countries



Source: SG Cross Asset Research/Commodities, Bloomberg
Country labels at the bottom of each chart run from the smallest producer (top left) to the largest producer (bottom right)

[8] The following document produced by SNL Metals & Mining methodology and definitions provides a detailed overview of SNL's principals and methodologies.

5) CFTC Commitment of Trader (COT) analysis

The following charts show the trends and extremes in the Money Manager (MM) and producer/merchant/processor/user (PMPU) sub-categories of the COT report for the major commodity markets. In Section 5a, we show the new (since 2014) LME COT data for copper, aluminium, zinc, lead and nickel. Extreme MM positions indicate that speculative positioning is strongly aligned and prices can be vulnerable to sudden price reversals if positions unwind quickly. Both extremes and trends in the PMPU positioning are often indicative of future price dynamics, as it is widely accepted that the PMPU category possesses an informational edge. By plotting changes in the long and short positions independently, changes in the overall net positioning become clearer.

Below are a few key highlights and observations from the charts below:

Long PMPU (consumer) hedging in ***WTI*** turns lower (Figure 5.2) with producer hedging continuing to drift sideways. Long MM liquidation in ***gold*** accelerates (Figure 5.5) and shorts increase. Long MM liquidation in ***nickel*** moves the MM position to its lowest level (Figure 5.16) and long MM positions in ***zinc*** (Figure 5.14) remain stable despite the recent price rally.

Figure 5.1 – Crude oil MM positions - % of total open interest

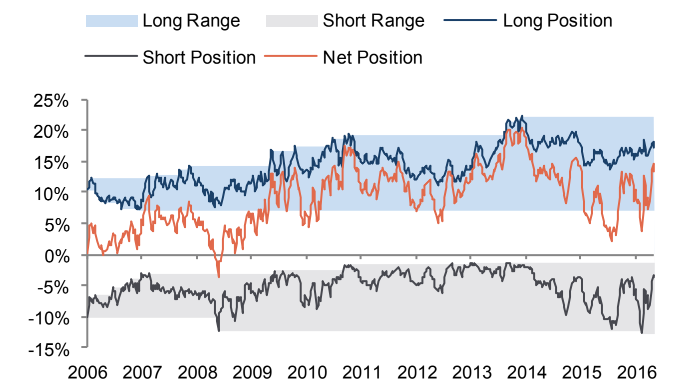


Figure 5.2 – Crude oil PMPU positions - % of total open interest

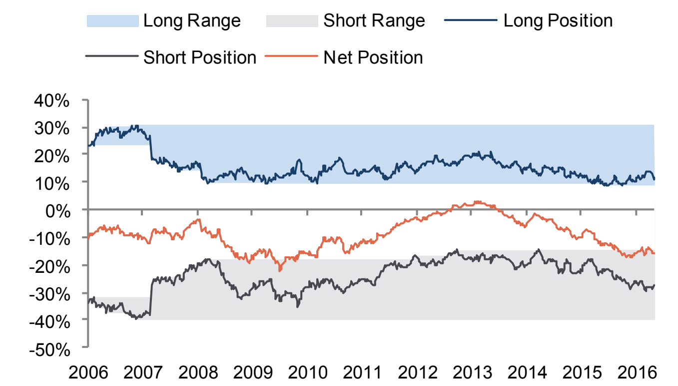


Figure 5.3 – Natural gas MM positions - % of total open interest

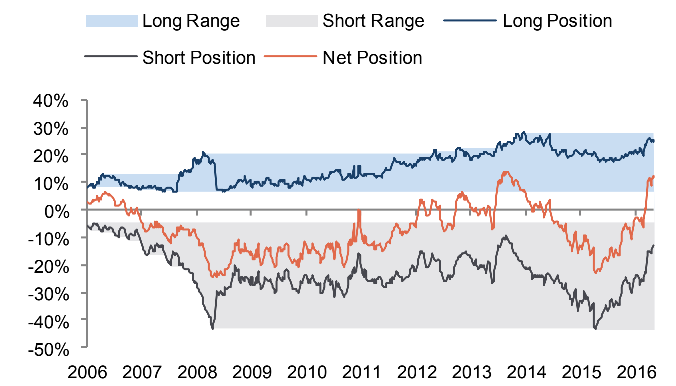
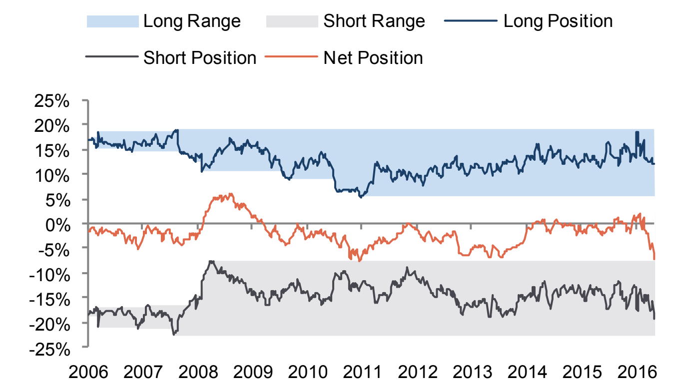


Figure 5.4 – Nat. gas PMPU positions - % of total open interest



Data is as of the most recent COT report with graphs extending back to the inception of the disaggregated data (June 2006). The shaded regions in each chart show the historical range of the individual long (light blue) and short (light grey) positions. The lines on each chart show the actual historical long (dark blue) and short (dark grey) positions, with the net position shown in orange. All positions are expressed as a percentage of open interest. Data includes only futures. **Producer/merchant/processor/user** is an entity that predominantly engages in the production, processing, packing or handling of a physical commodity and uses the futures markets to manage or hedge risks associated with those activities. **Money manager** for the purpose of this report is a registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organised futures trading on behalf of clients.
Source: SG Cross Asset Research/Commodities, Bloomberg, www.cftc.gov

Figure 5.5 – Gold MM positions- % of total open interest

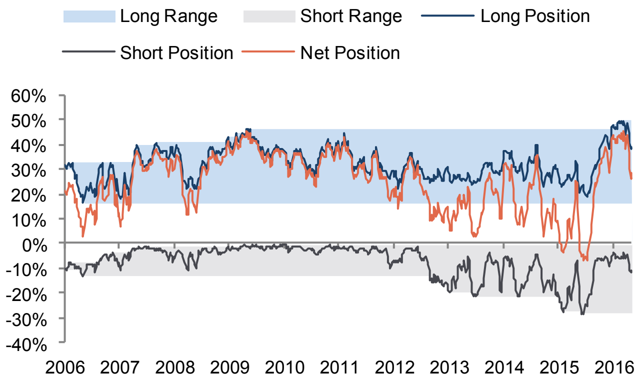


Figure 5.6 – Gold PMPU positions- % of total open interest

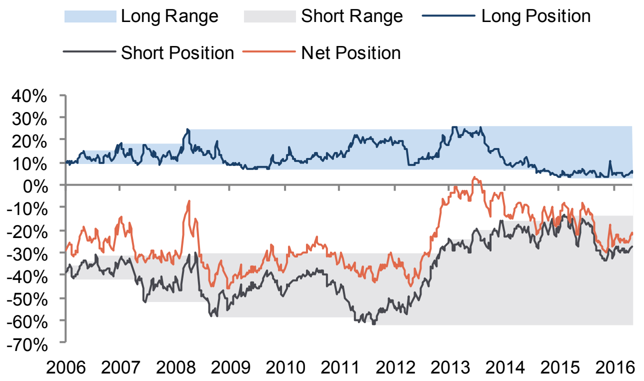


Figure 5.7 – Corn MM positions- % of total open interest

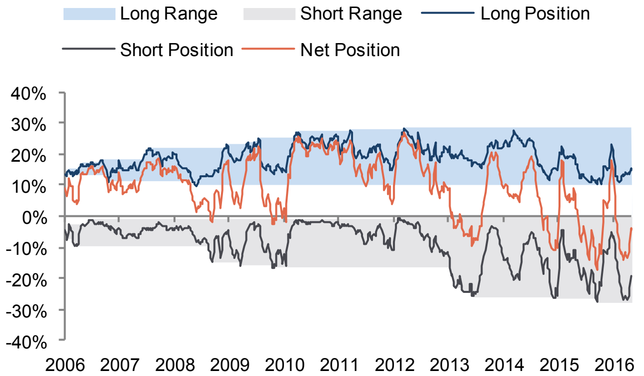


Figure 5.8 – Wheat MM positions- % of total open interest

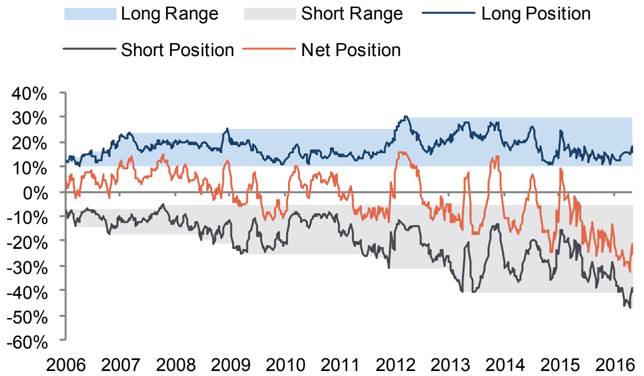


Figure 5.9 – Soybean MM positions- % of total open interest

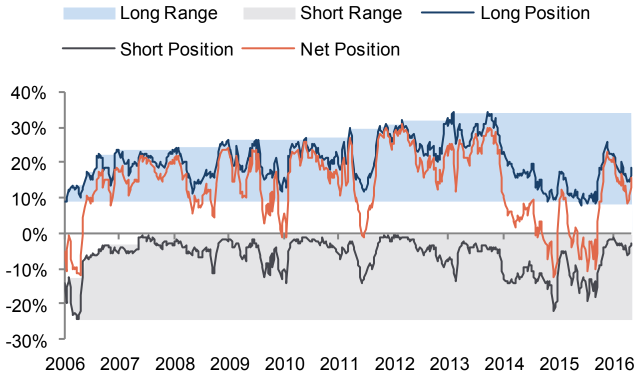
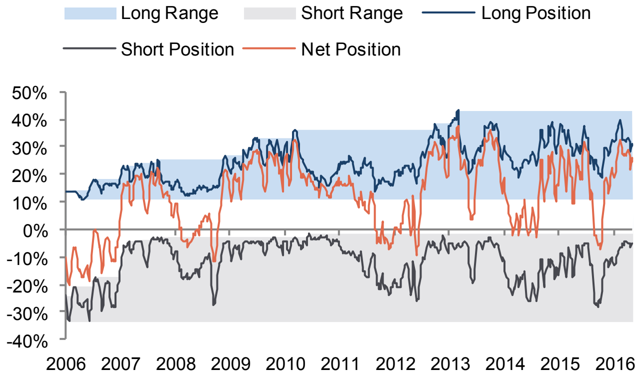


Figure 5.10 – Cotton MM positions- % of total open interest



Data is as of the most recent COT report with graphs extending back to the inception of the disaggregated data (June 2006). The shaded regions in each chart show the historical range of the individual long (light blue) and short (light grey) positions. The lines on each chart show the actual historical long (dark blue) and short (dark grey) positions, with the net position shown in orange. All positions are expressed as a percentage of open interest. Data includes only futures. **Producer/merchant/processor/user** is an entity that predominantly engages in the production, processing, packing or handling of a physical commodity and uses the futures markets to manage or hedge risks associated with those activities. **Money manager** for the purpose of this report is a registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organised futures trading on behalf of clients.
Source: SG Cross Asset Research/Commodities, Bloomberg, www.cftc.gov

5a) London Metal Exchange (LME) COT Analysis

The following LME COT data is available since July 2014.

Figure 5.11 – Copper MM positions- % of total open interest

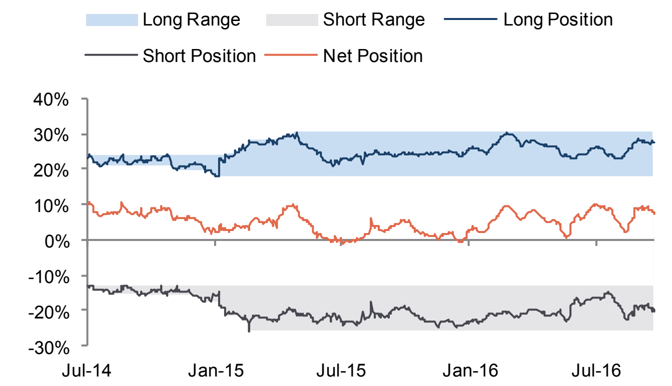


Figure 5.12 – Copper PMPU positions- % of total open interest

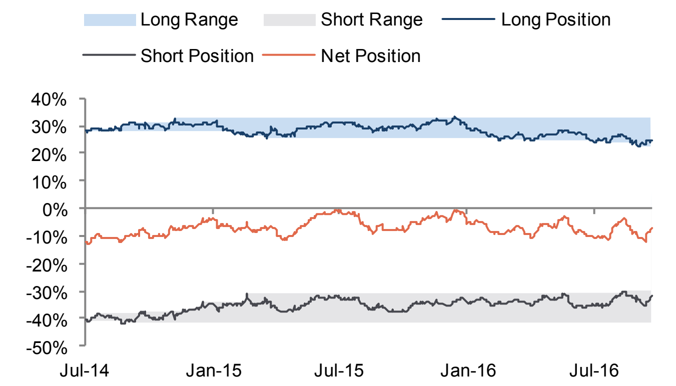


Figure 5.13 – Aluminium MM positions- % of total open interest

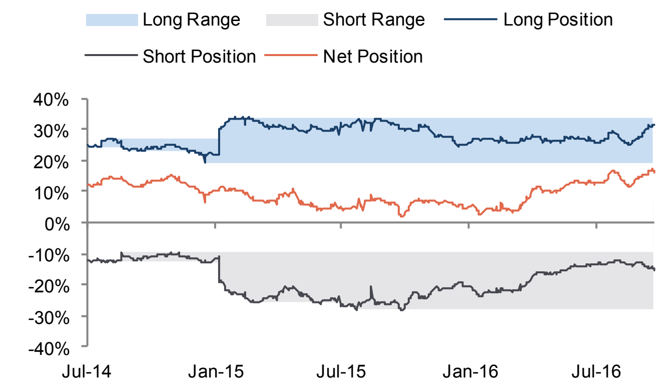


Figure 5.14 – Zinc MM positions- % of total open interest

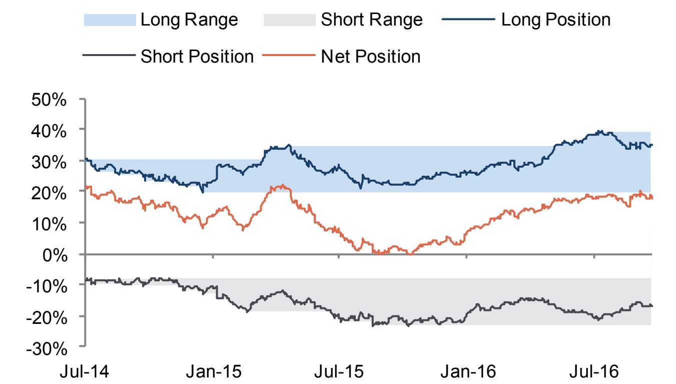


Figure 5.15 – Lead MM positions- % of total open interest

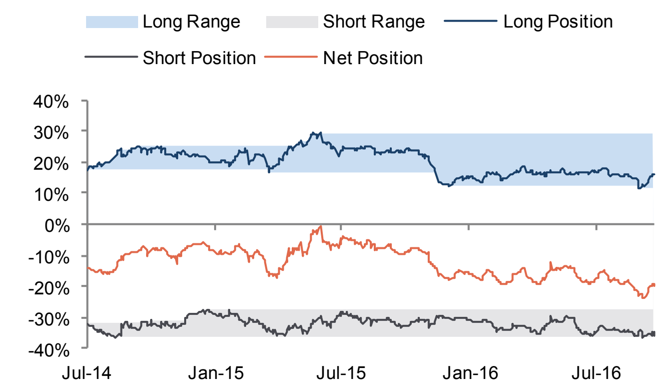
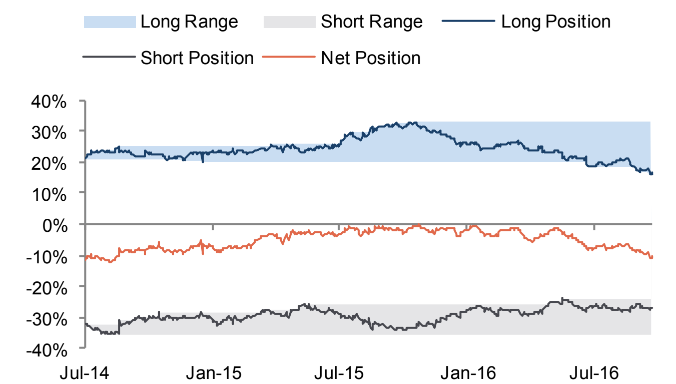


Figure 5.16 – Nickel MM positions- % of total open interest



Data is as of the most recent COT report with graphs extending back to the inception of the data (July 2014). The shaded regions in each chart show the historical range of the individual long (light red) and short (light brown) positions. The lines on each chart show the actual historical long (dark red) and short (dark brown) positions, with the net position shown in blue. All positions are expressed as a percentage of open interest. Data includes only futures.
Producer/merchant/processor/user Entities that are predominantly engaged in production, processing, packaging or handling of metal and that use the LME to manage or hedge risks associated with those activities. **Money manager** Entities that are engaged in managing and conducting LME contracts on behalf of underlying Clients such as investment fund firms.
Source: SG Cross Asset Research/Commodities, Bloomberg, www.lme.com

6) Dry Powder analysis – insights into positioning

In the October 2016 Commodities Compass - Measuring "dry powder" in commodities – some alternative insights into positioning, we looked at alternative ways of analysing commodity COT Money Manager (MM) positioning data. We provided additional insights into gauging the likelihood of further investment flows based on historical allocation patterns, the number of entities currently in the market, the current position limits and of course current prices.

This approach essentially allows us to determine the amount of "dry powder" there is in each commodity to support a potential move. The approach also provides additional insight into market positioning and significant value in assessing trade conviction and identifying new trading opportunities.

A key benefit of this approach is that it helps us answer some of the following types of questions: Are there many entities left to buy/sell the market? How much capital could be potentially allocated to a position at current prices? How close are the current positions to position limits? How vulnerable are current positions to profit-taking (long liquidation or short covering)? How strong could the potential price retracements and rallies be? Here we provide updates of charts for some of the key commodities

Below we highlight a few interesting observations from the charts below:

WTI

The size of the long futures positions in WTI (Figure 6.1) for the currently 60 long Money Managers (MMs) is currently (big blue dot) near its historical maximum level. In the absence of new MMs entering the market, this suggests the existing long MM are unlikely to drive prices higher. Contrasting the futures position however to the dollar position (Figure 6.2), the picture is different – the low oil price means that the existing long dollar position is not at a historical maximum – this suggests that existing long MMs could in fact increase their dollar exposure. Conversely, this might also means that the impact of any potential long liquidation is potentially reduced due to the reduced notional value (and hence market impact) of the position.

Sugar & cotton

The long and short futures and dollar positions (Figures 6.11 & 6.12) are at opposite extremes, with the longs at historically maxima and the shorts at historical minima. This suggests that MM driven upside is largely limited (due to simple absence of any dry powder), whereas the downside risk via long liquidation and fresh shorts could be considerable. This is also the case for cotton (Figures 6.9 & 6.10) although these positions are not quite as extreme.

Corn

The short position in terms of both futures and dollars (Figures 6.5 and 6.6) are at maximum levels for the currently short 65 MMs. This combined with a relatively conservative long position, suggest that upside risk driven by short covering and fresh longs is high.

Figure 6.1 – WTI - long (blue) and short (red) MM position in lots (y-axis) versus number of MMs (x-axis).
Spot month position limit (dotted line) – 3000 lots

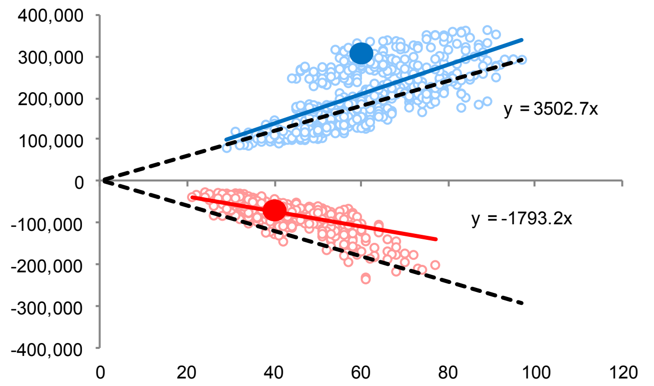


Figure 6.2 – WTI - long (blue) and short (red) MM exposure in $bn (y-axis) versus number of MMs (x-axis)

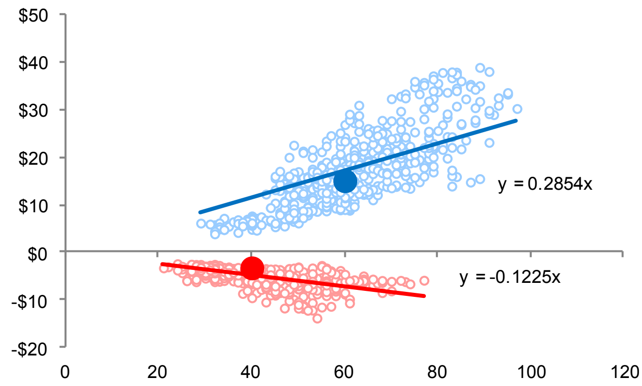


Figure 6.3 – NG - long (blue) and short (red) MM position in lots (y-axis) versus number of MMs (x-axis).
Spot month position limit (dotted line) – 1000 lots

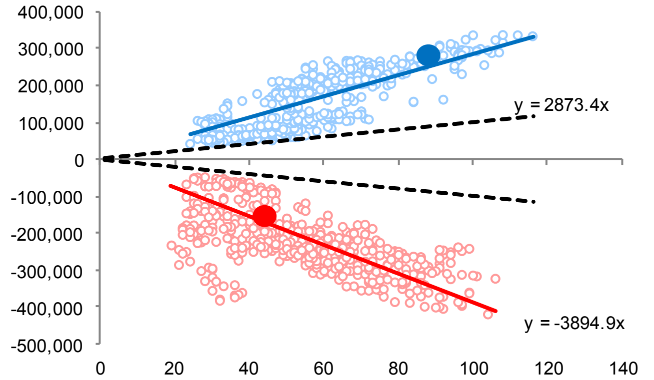


Figure 6.4 – NG - long (blue) and short (red) MM exposure in $bn (y-axis) versus number of MMs (x-axis)

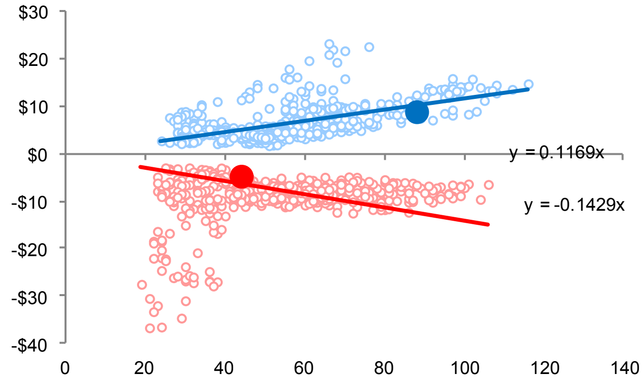


Figure 6.5 – Corn - long (blue) and short (red) MM position in lots (y-axis) versus number of MMs (x-axis).
Spot month position limit (dotted line) – 600 lots

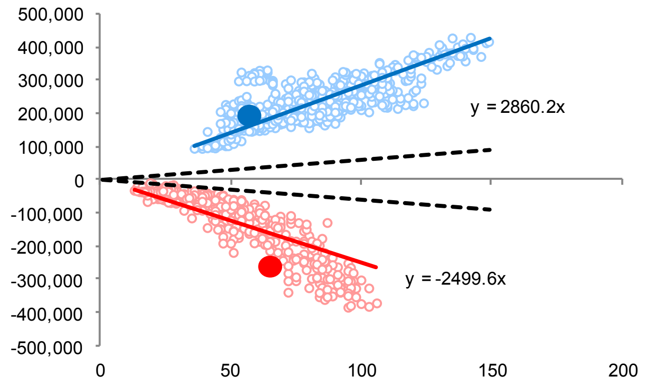
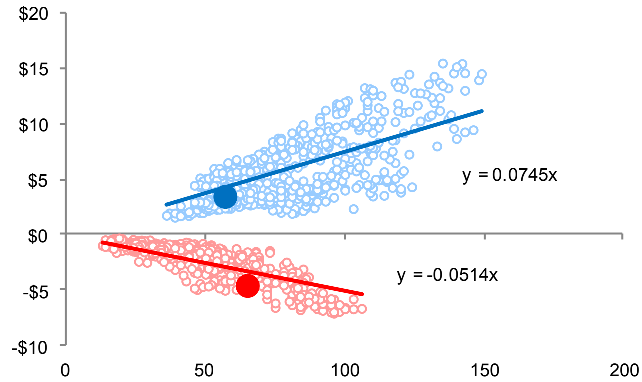


Figure 6.6 – Corn - long (blue) and short (red) MM exposure in $bn (y-axis) versus number of MMs (x-axis)



Data is as of the most recent COT report with graphs extending back to the inception of the disaggregated data (June 2006). Data includes only futures. The large blue and red dots indicate the most recent week. The dotted lines indicate the spot month position limit per trader.
Money manager (MM) for the purpose of this report is a registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organised futures trading on behalf of clients.
Source: SG Cross Asset Research/Commodities, Bloomberg, www.cftc.gov

Figure 6.7 – Soybeans - long (blue) and short (red) MM position in lots (y-axis) versus number of MMs (x-axis).
Spot month position limit (dotted line) – 600 lots

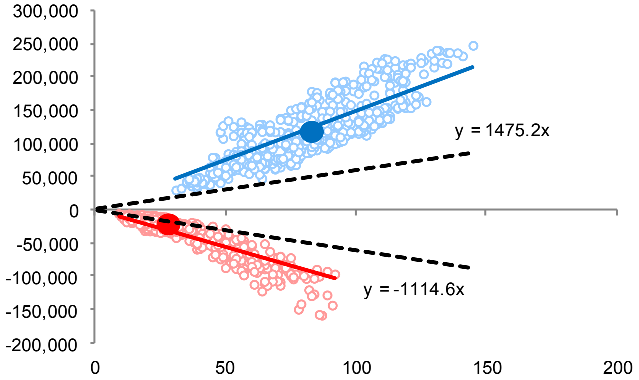


Figure 6.8 – Soybeans - long (blue) and short (red) MM exposure in $bn (y-axis) versus number of MMs (x-axis)

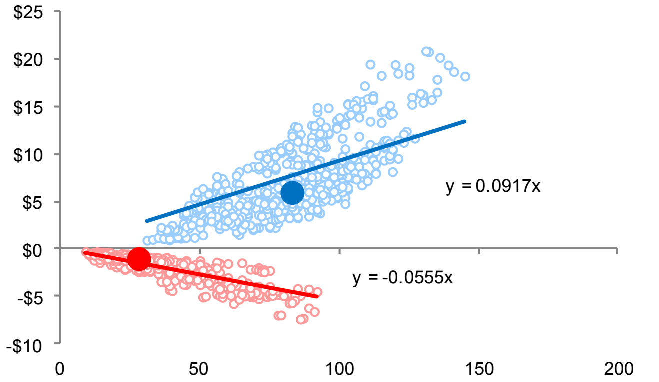


Figure 6.9 – Cotton - long (blue) and short (red) MM position in lots (y-axis) versus number of MMs (x-axis).
Spot month position limit (dotted line) – 300 lots

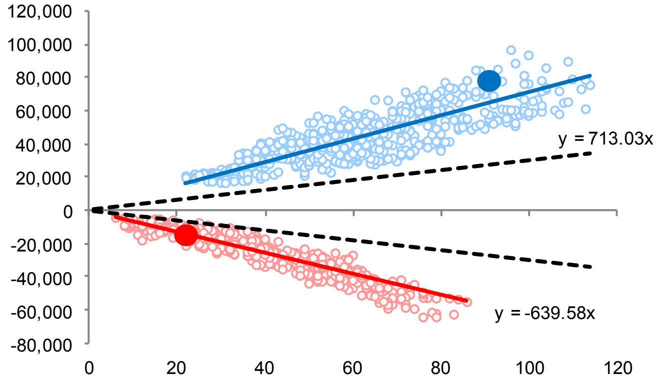


Figure 6.10 – Cotton - long (blue) and short (red) MM exposure in $bn (y-axis) versus number of MMs (x-axis)

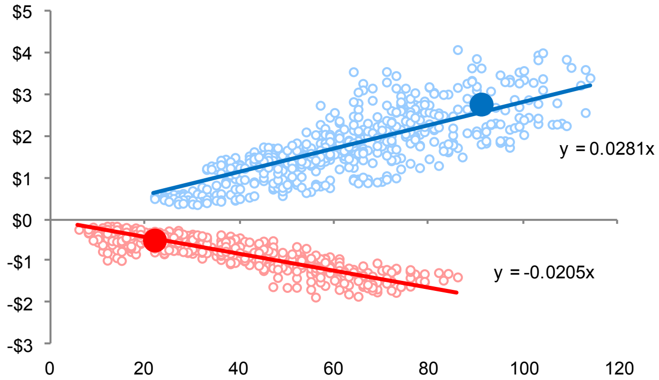


Figure 6.11 – Sugar - long (blue) and short (red) MM position in lots (y-axis) versus number of MMs (x-axis).
Spot month position limit (dotted line) – 5000 lots

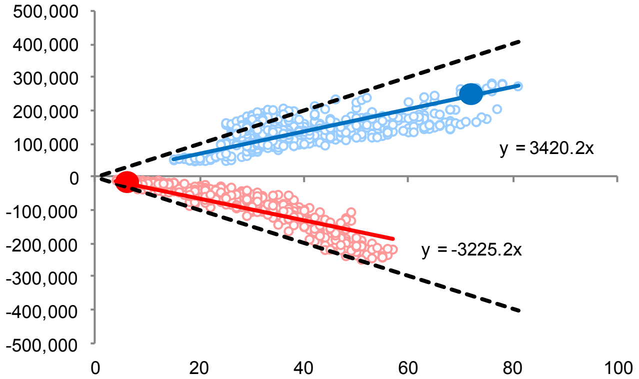
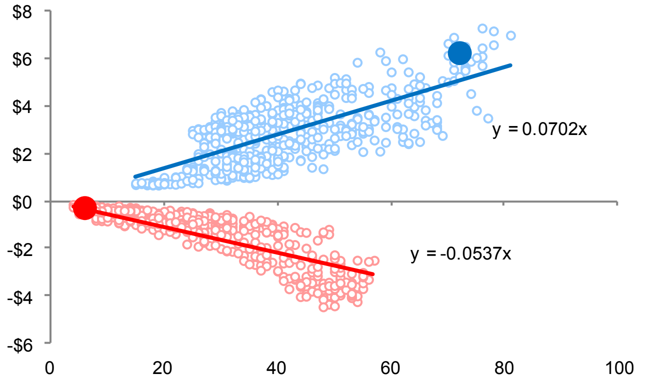


Figure 6.12 – Sugar - long (blue) and short (red) MM exposure in $bn (y-axis) versus number of MMs (x-axis)



Data is as of the most recent COT report with graphs extending back to the inception of the disaggregated data (June 2006). Data includes only futures. The large blue and red dots indicate the most recent week. The dotted lines indicate the spot month position limit per trader.
Money manager for the purpose of this report is a registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organised futures trading on behalf of clients.
Source: SG Cross Asset Research/Commodities, Bloomberg, www.cftc.gov

Figure 6.13 – Gold - long (blue) and short (red) MM position in lots (y-axis) versus number of MMs (x-axis).
Spot month position limit (dotted line) – 3000 lots

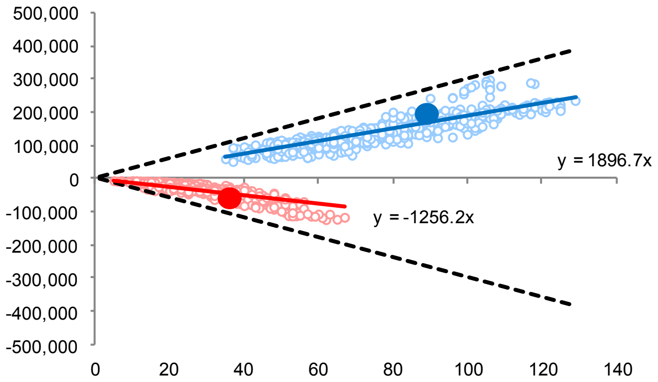


Figure 6.14 – Gold - long (blue) and short (red) MM exposure in $bn (y-axis) versus number of MMs (x-axis)

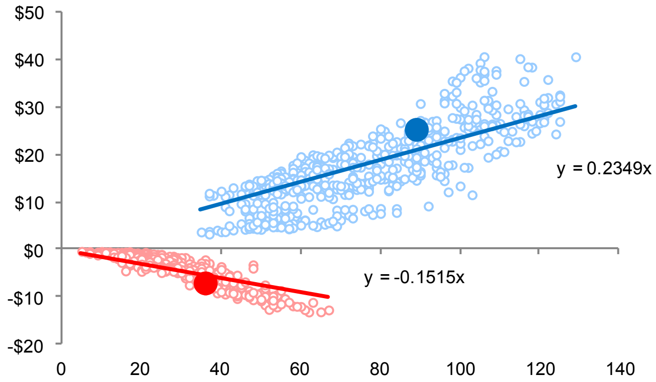


Figure 6.15 – Silver - long (blue) and short (red) MM position in lots (y-axis) versus number of MMs (x-axis).
Spot month position limit (dotted line) – 1500 lots

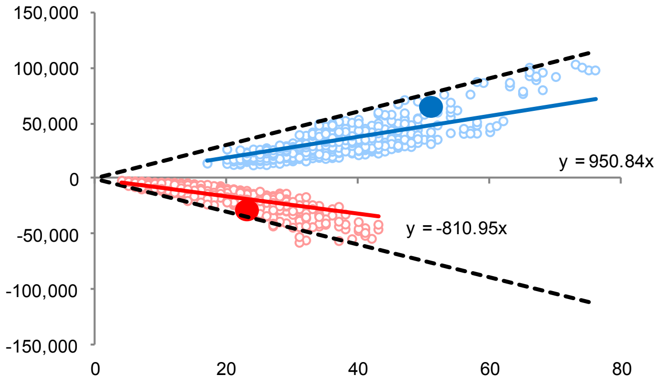


Figure 6.16 – Silver - long (blue) and short (red) MM exposure in $bn (y-axis) versus number of MMs (x-axis)

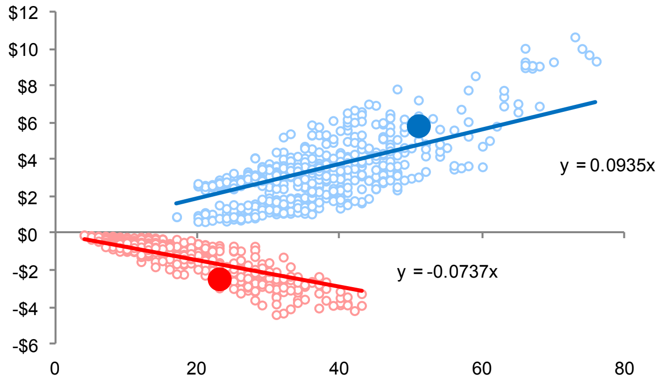


Figure 6.15 – Live cattle - long (blue) and short (red) MM position in lots (y-axis) versus number of MMs (x-axis).
Spot month position limit (dotted line) – 450 lots

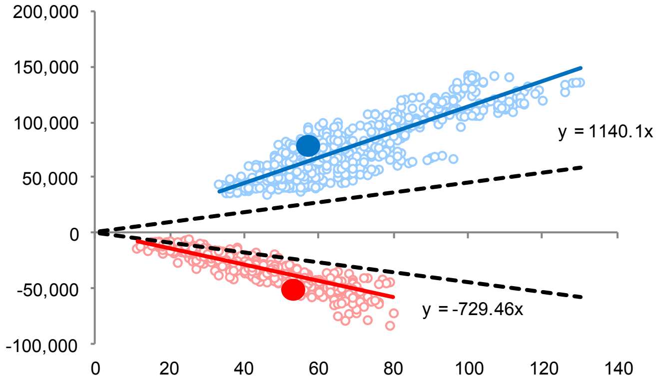
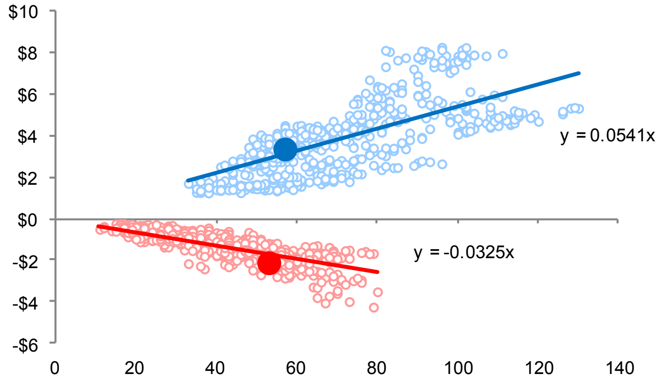


Figure 6.16 – Live cattle - long (blue) and short (red) MM exposure in $bn (y-axis) versus number of MMs (x-axis)



Data is as of the most recent COT report with graphs extending back to the inception of the disaggregated data (June 2006). Data includes only futures. The large blue and red dots indicate the most recent week. The dotted lines indicate the spot month position limit per trader.
Money manager for the purpose of this report is a registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organised futures trading on behalf of clients.
Source: SG Cross Asset Research/Commodities, Bloomberg, www.cftc.gov

7) SG price forecasts

The following charts show the average annual SG price forecasts over the next three years. The current year is based on the average of the **forthcoming quarterly forecasts**. For detailed forecasts, please refer to our quarterly Commodities Review publications.

Forecast years are indicated by the following colours: 2016 2017 2018

Figure 7.1 – Crude oil (WTI)

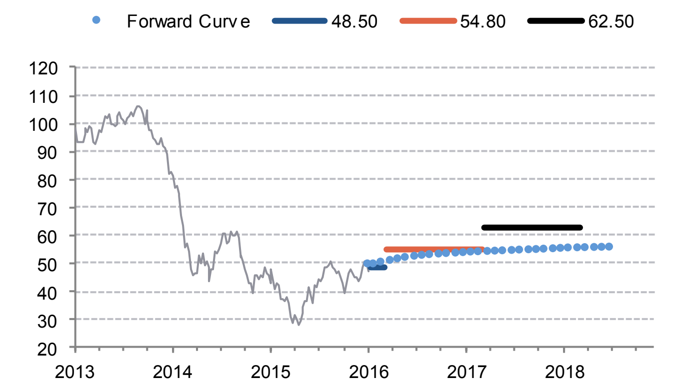


Figure 7.2 – Brent

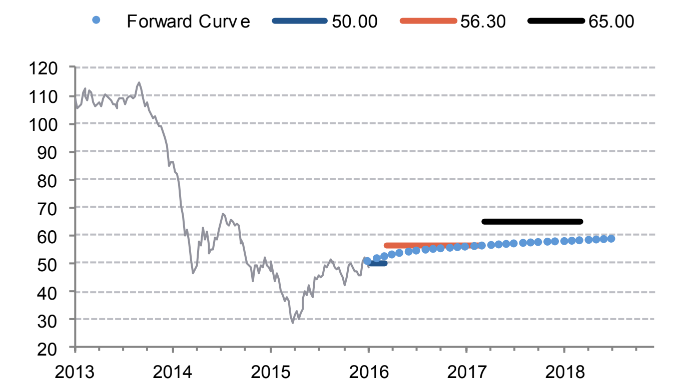


Figure 7.3 – Natural gas (NYMEX)

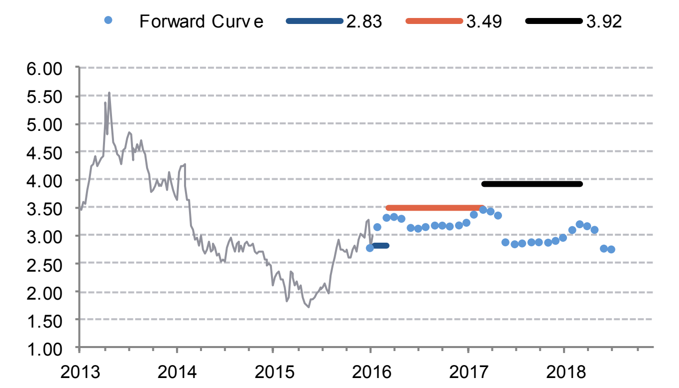


Figure 7.4 – Copper (LME)

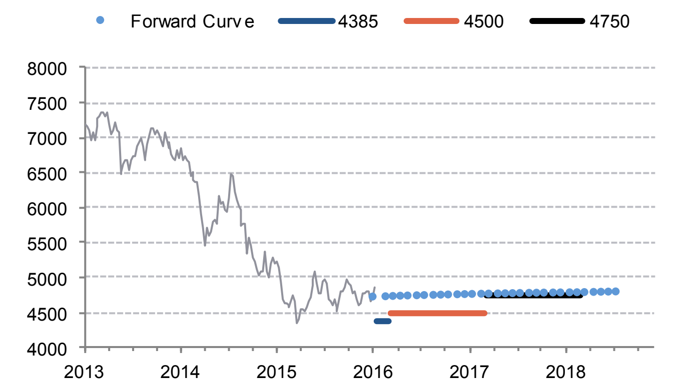


Figure 7.5 – Aluminium

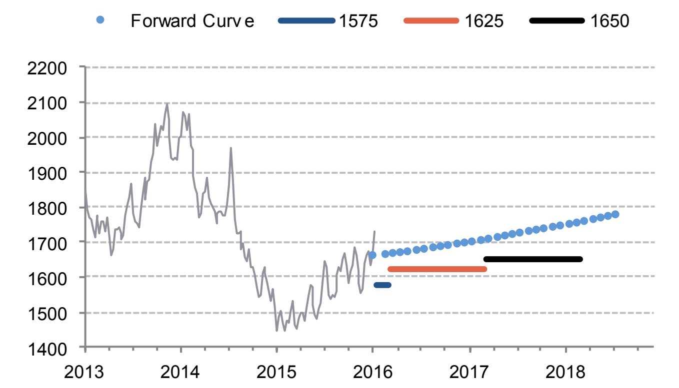
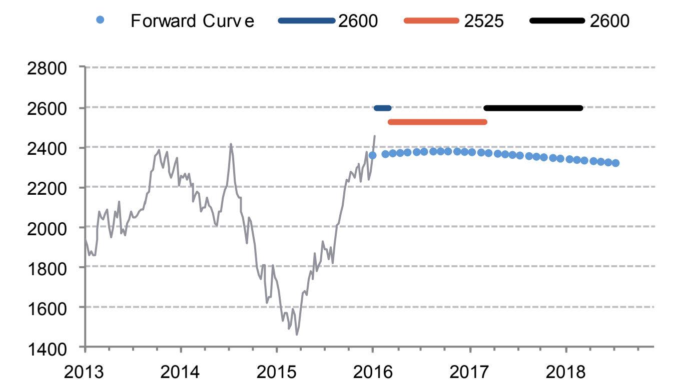


Figure 7.6 – Zinc



Price history (grey line) is based on the front month futures contract (unadjusted).
Source: SG Cross Asset Research/Commodities, Bloomberg

Forecast years are indicated by the following colours: 2016 2017 2018

Figure 7.7 – Lead (LME)

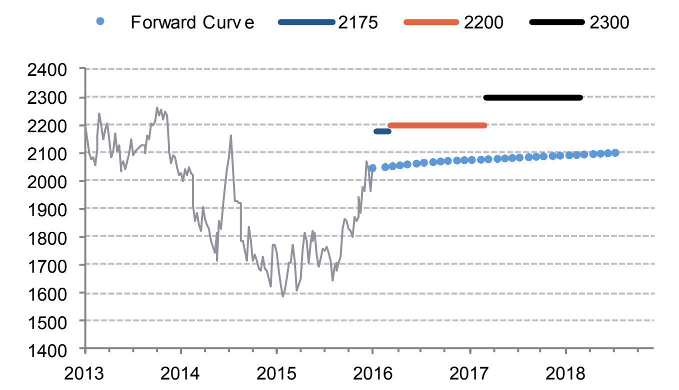


Figure 7.8 – Nickel (LME)

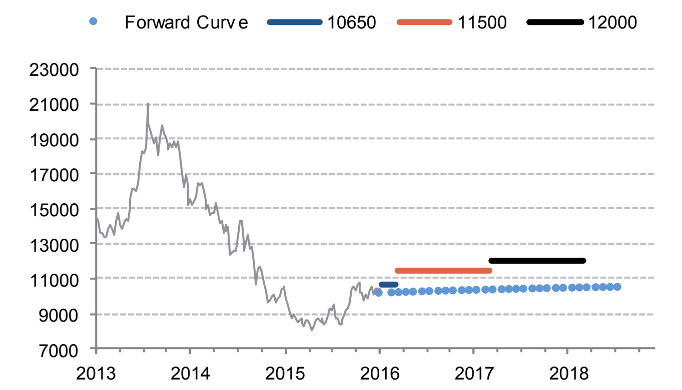


Figure 7.9 – Corn

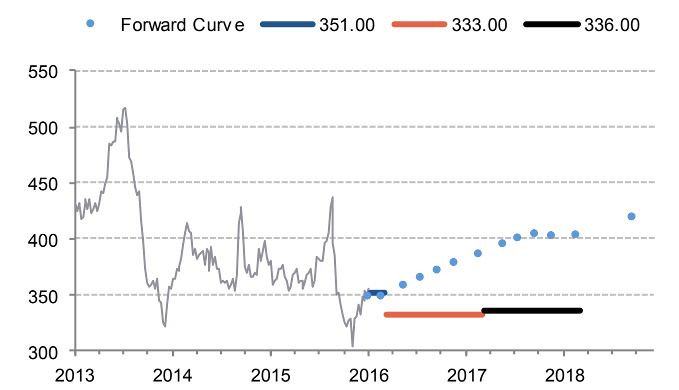


Figure 7.10 – Wheat

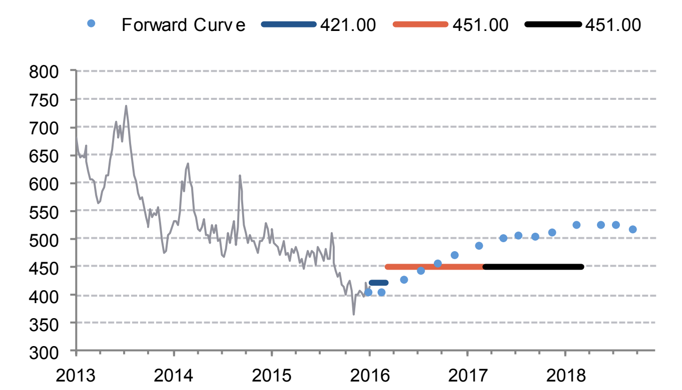


Figure 7.11 – Soybeans

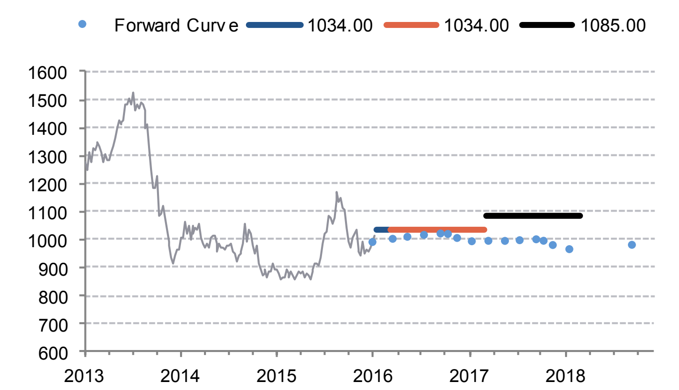
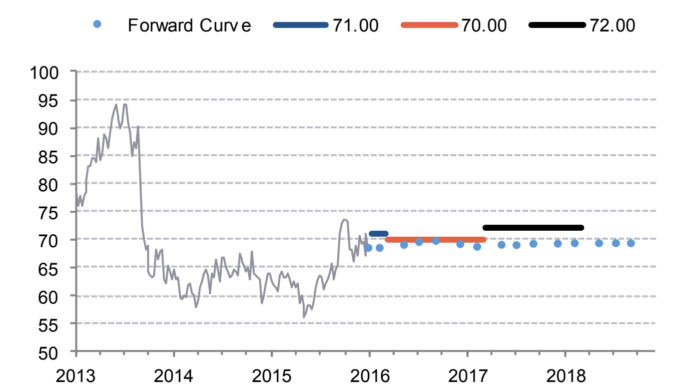


Figure 7.12 – Cotton



Price history (grey line) is based on the front month futures contract (unadjusted).
Source: SG Cross Asset Research/Commodities, Bloomberg

Forecast years are indicated by the following colours: 2016 2017 2018

Figure 7.13 – Sugar

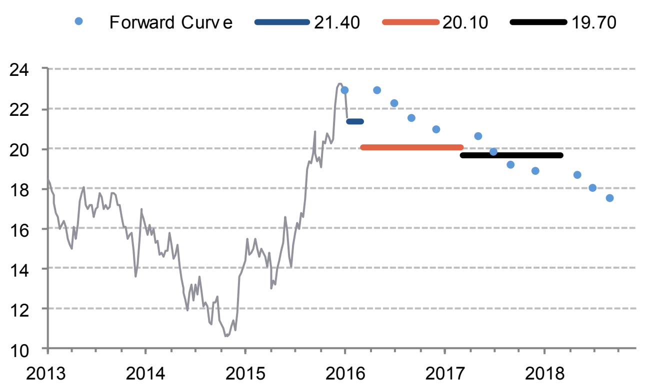


Figure 7.14 – Coffee

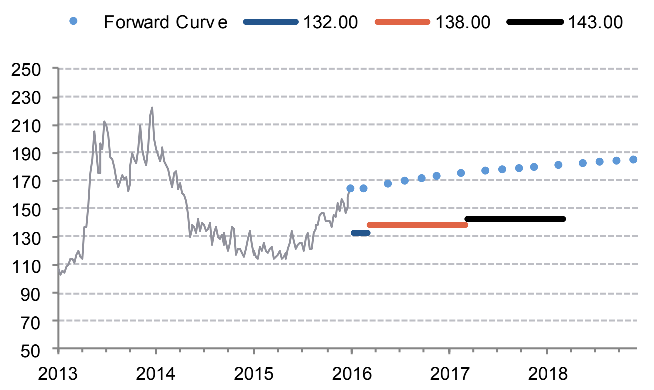


Figure 7.15– Live cattle

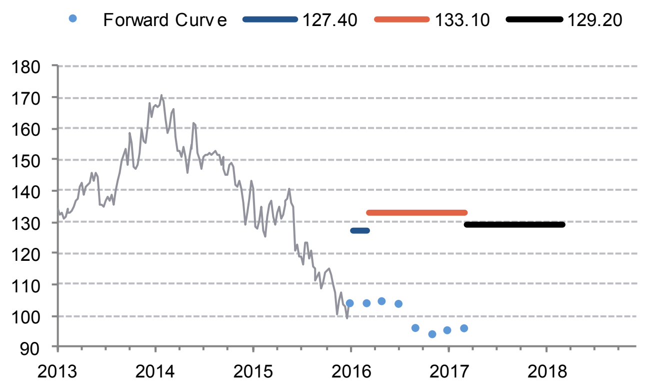


Figure 7.16– Lean hogs

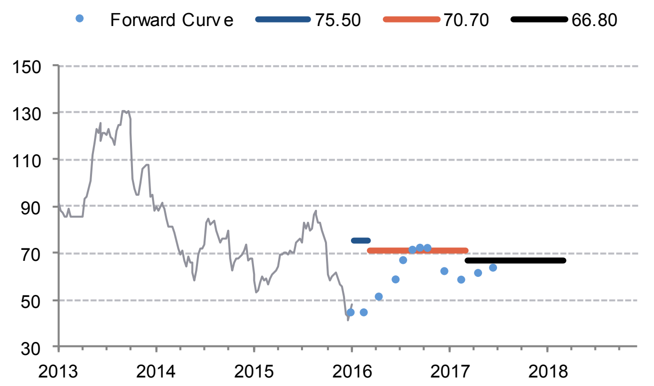


Figure 7.17 – Gold

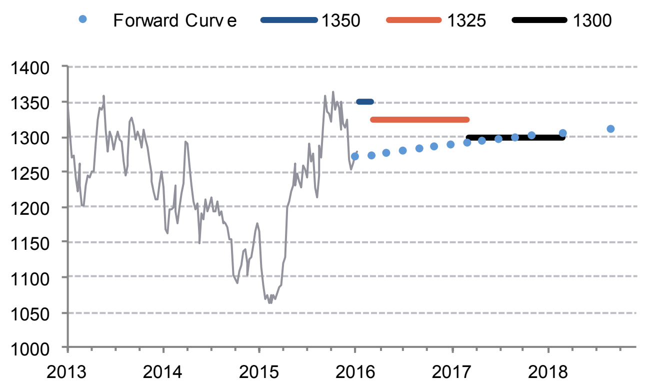
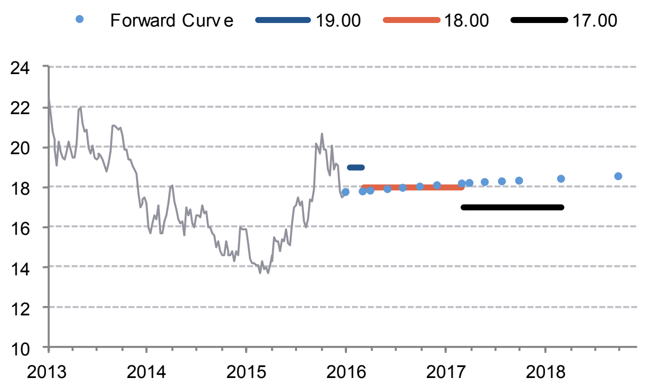
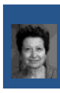


Figure 7.18 – Silver



Price history (grey line) is based on the front month futures contract (unadjusted).
Source: SG Cross Asset Research/Commodities, Bloomberg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