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Introducing the POINT® Commodity Risk Model

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- Commodities have become an integral part of institutional portfolios, mainly because of their ability to provide diversification benefits, potential inflation-hedging properties, and additional sources of return. In this paper, we introduce a new multi-factor risk model[1] for commodity futures in POINT®, the Barclays global multi-asset class portfolio management and analytics platform.
- The model incorporates certain innovations designed to capture the risk characteristics of both active and benchmark commodity futures portfolios, including curve positioning and spread trades. It is built based on the Barclays single-commodity benchmark indices.
- The model incorporates a level and a slope factor (with certain necessary exceptions) for each commodity type. These factors correspond to investible rolling positions on different commodity types at different maturities and, as such, are constructed to be intuitive and to provide straightforward interpretations for commodity investors.
- Factor loadings are estimated via a multivariate regression that uses daily data. This was made possible by the availability of liquid daily data based on Barclays commodity indices. The use of higher frequency data provides two major advantages: more responsive and more precise risk forecasts.
- The idiosyncratic risk forecast also utilizes daily data, the daily residual returns. The model also takes into account the correlations between the idiosyncratic returns of different contracts that belong to the same commodity type. This becomes especially important in capturing the risk of curve trades within a specific commodity type.
- Seasonality is an important characteristic of certain commodity sectors, namely agriculture, livestock, and some energy commodities. We observe significant seasonal patterns in the volatility of certain commodity factor returns and have developed a proprietary algorithm to adjust our volatility forecasts to take into account such seasonal patterns in order to produce more precise risk forecasts.
- The model is fully integrated with other asset classes and major functionalities in POINT®, including the risk model, portfolio optimizer, and factor-based scenario analysis.
- The model performs well in forecasting the risk of long-only futures portfolios across different commodity types and maturities, as well as long/short portfolios that capture curve and spread trades.

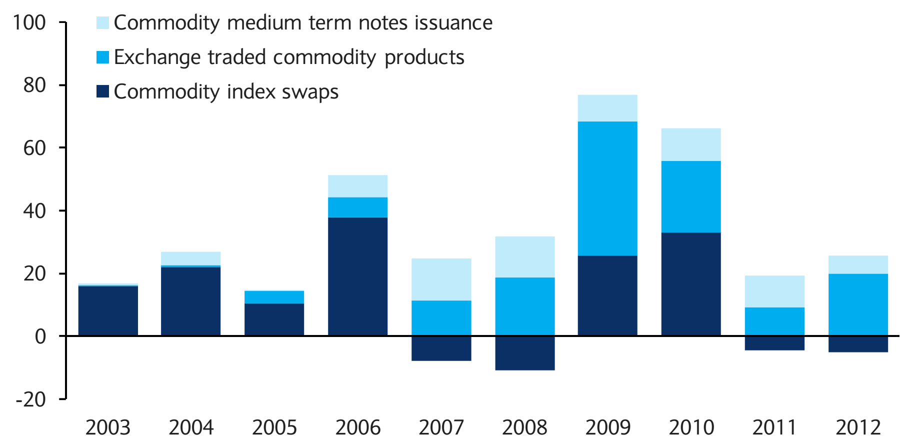
[1] The authors would like to thank Antonio Silva and Anthony Lazanas for their valuable contributions in the design and the development of the model.

1- Introduction

Commodities have developed into a liquid asset class forming part of the core allocations of balanced portfolios. This increase in the importance of commodities as a financial asset class has gone hand in hand with the increased liquidity and transparency in gaining access to commodity investments. Only a small number of investors trade commodities outright; most market participants gain exposure to commodities via the futures market. Most institutional commodity portfolios are composed of futures contracts on multiple commodities, often with different maturities, rather than physical commodities. Over time, those portfolios have developed from consisting primarily of benchmark access to a broad basket of short-maturity futures positions to more complex portfolios that aim to extract value from more dynamic positioning on individual commodities and different maturities. Figure 1 shows inflows to the commodity markets over the past decade through different types of investment vehicles (see Cooper, Luo, Norrish, and Corsi (2013)). It is important to note that exchange-traded products, including futures, have been the dominant medium for inflows, especially in the second half of this period.

FIGURE 1

Inflows to the Commodity Markets ($bn)



Source: Bloomberg, MTN-i, ETP issuer data, Barclays Research

To understand the risk and return of commodity futures portfolios, it is essential to appreciate that every commodity is represented by a term structure of forward trades, with different dynamics governing each of these curves. Although the longer end of the futures curve is relatively stable for most commodities, as it is essentially driven by the marginal cost of production and the expectation of normal inventory levels, in the short/medium term, the curve shape is more volatile. While every commodity is subject to unique fundamental factors, in general the shape and dynamics of the curve are determined by the interactions among the following factors.

- **Fundamentals linked to the economic cycle.** Commodity futures curves are closely linked to the fundamentals of the specific markets and the economic cycle. Through the cycle, periods of strong and weak demand will affect production incentives and the level of inventories, which will drive changes in the futures curves. When inventories are low, the curve typically trades in backwardation, which will often spur the build-up of inventories. Commodities with ample inventories and good storability tend to trade in contango.

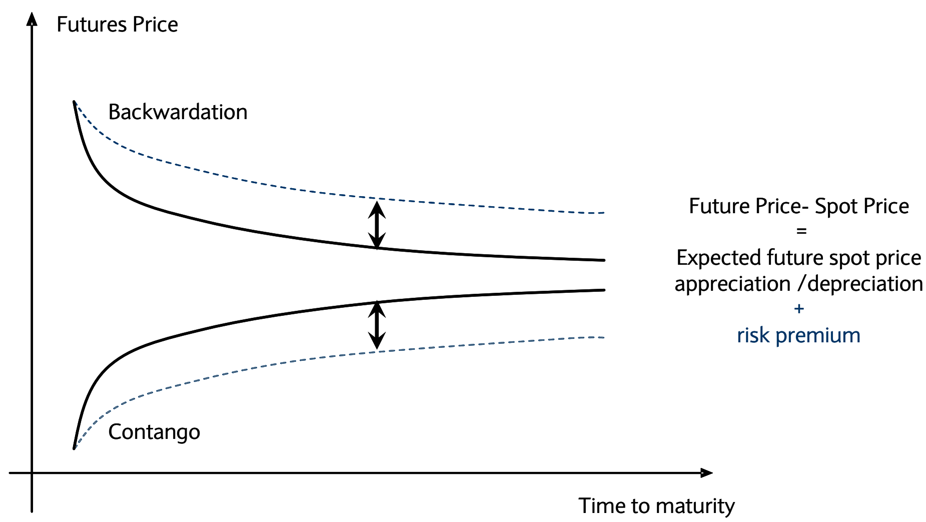
- **Seasonality.** Demand for seasonal commodities is generally confined to certain months, creating fluctuations in the supply/demand balance through the year. This gives rise to price and liquidity seasonal patterns reflected in the shape of the futures curves. In general, the curves show peaks and troughs linked to expected supply/demand lows and highs.

- **Activity of market participants with various time horizons and objectives.** Producers and consumers, driven by different incentives and over different horizons, seek to transfer price risk. Producers often seek to hedge their risk exposure in the middle and long term to ensure profitability over time, while consumers tend to focus on short-term exposure. Market participants with pure financial investment objectives can be classified as active or passive investors. Benchmark index investors typically invest in the front end of the futures curves, while active speculators aim to obtain positive returns by anticipating price moves across the curve. Given the relatively large flows associated with benchmark investing, liquidity across individual commodities is concentrated in the short end of the curve, where most of the passive benchmark commodity indices take positions. Liquidity at longer maturities typically decreases sharply with the horizon and varies strongly over time.

Price dynamics of futures contracts at different maturities are also driven by the storage and financing costs of maintaining physical commodity supplies. The projected evolution of supplies and participants' varying investment horizons give rise to risk premia being incorporated into futures prices with delivery dates at longer horizons. These risk premia compensate investors for assuming price uncertainty until maturity. As shown in Figure 2, the futures price (solid lines) can be decomposed into two components: expected future spot price (dotted lines) and the risk premium, in the case of backwardation vs contango. Commodity futures risk models need to be able to capture different dynamics of individual commodity curves.

FIGURE 2

Curve Shapes and Risk Premia



Source: Barclays Research

The POINT® Commodity Risk Model incorporates certain innovations designed to capture the risk characteristics of both active and benchmark commodity futures portfolios, including curve positioning and spread trades. It is built based on the Barclays single-commodity benchmark indices.

The model is fully integrated with other asset classes and major functionalities in POINT®, including the risk model, portfolio optimizer, and factor-based scenario analysis. It is part of a multi-asset class platform that provides valuable analysis for both focused commodity portfolios and well-diversified cross-asset class portfolios.

The systematic part of the model consists of a level and a slope factor (with certain necessary exceptions) for each commodity type. These factors correspond to investible rolling positions on different commodity types at different maturities and, as such, are constructed to be intuitive and to provide straightforward interpretations for commodity investors. Loadings to these factors are estimated via a multivariate regression that uses daily data. The use of higher frequency data brings two major advantages: more responsive and more precise risk forecasts. This was made possible by the availability of liquid daily data based on Barclays commodity indices.

The idiosyncratic risk forecast also utilizes daily data, daily residual returns. The model also takes into account the correlations between the idiosyncratic returns of different contracts that belong to the same commodity type. This becomes especially important in capturing the risk of curve trades within a specific commodity type, as systematic risk tends to be hedged out to a certain extent and idiosyncratic risk becomes more important for such trades.

Seasonality is an important characteristic of certain commodity sectors, namely agriculture, livestock, and some energy commodities. Seasonal patterns can be observed in the evolution of spot prices or along the commodity futures curve. However, more relevant from the perspective of risk modeling are patterns in the distribution of returns. In that regard, we observe significant seasonal patterns in the volatility of certain commodity factor returns and have developed a proprietary algorithm to adjust our volatility forecasts to take into account such seasonal patterns in order to produce more precise risk forecasts.

This paper is organized as follows. Section 2 describes the risk model in detail, discussing the underlying data used in calibrating the model, construction of systematic risk factors and their properties, and estimation of factor loadings. Section 3 discusses the estimation of systematic and idiosyncratic risk for commodity portfolios, including the adjustment in risk forecasts to account for seasonality. Section 4 presents an extensive back-testing analysis to illustrate how well the model predicts the volatility of different types of commodity portfolios. Finally, Section 5 illustrates an application of the model in the POINT® platform, using the Barclays DJ-UBS CI Pure Beta Index.

2- Model Description

The POINT® Global Risk Model consists of hundreds of factors across various asset classes. In the selection of these factors, qualitative criteria such as economic intuition, as well as quantitative criteria such as the explanatory power of the model, play important roles. A major goal in this endeavor is to ensure that the factors going into our models correspond to how portfolio managers think about the relevant market, are intuitive, and have sound economic interpretation. Therefore, we tend to build our models based on economic factors rather than purely statistical factors. In purely statistical models, such as principal component analysis (PCA), economic interpretation of factors may not be straightforward.

Another important distinction in the risk modeling effort is the way the model is estimated, namely cross-sectional vs time-series models. Figure 3 compares these two types of models (please refer to Ural (2010) for a detailed discussion of linear factor models). As the figure shows, there are advantages to both approaches. For modeling the risk of commodity futures, we use the time-series approach. First of all, factors are more straightforward to define than loadings, where the level and the slope of the commodity curve have sound economic interpretation as factors. Also, in the commodities market, there is a relatively small cross-section of securities one can use to estimate the (two) risk factors. For other major asset classes such as equities or credit, hundreds of instruments can be used to estimate the risk factors via cross-sectional regressions, ensuring a more robust regression exercise.

FIGURE 3

Cross-Sectional vs Time-Series Models

	Cross-Sectional	Time-Series
Input Data	Security-specific loadings	Historical factor returns
# of Parameters to Estimate	(no. of factors) * (no. of months)	(no. of securities) * (no. of factors)
Interpretation	Cleaner interpretation of loadings and univariate factors	Straightforward interpretation of factors

Source: Barclays Research

The following equation describes the multi-factor risk model used for commodity futures in POINT®:

$$r_t = \beta_t^L * F_t^L + \beta_t^S * F_t^S + \varepsilon_t$$

where r_t is the return on a given futures contract, F_t^L, F_t^S are, respectively, the relevant level (L) and slope (S) factors, β_t^L, β_t^S are the loadings to these factors, and ε_t is the idiosyncratic return. As we can see, the systematic part of the model is composed of two risk factors – level and slope – that are constructed separately for each commodity type, based on Barclays single-commodity benchmark indices. The loadings to these factors are estimated through a multivariate (time-series) regression that uses daily returns.

The use of Barclays indices provides us with clearly defined and intuitive instruments to build risk factors. We have built on our considerable experience and strength in commodity indexing. Barclays offers investors a complete family of commodity benchmark and tradable indices spanning beta, enhanced beta, and alternative beta in a single platform. These indices can be used as performance targets, informational measures of asset class performance, or as the reference for structured and exchange traded products for the asset class. Please refer to Williams, Tian, and Rivera (2011) for more details on Barclays commodity indices.

Commodity Indices

Figure 4 shows the list of 33 commodity types covered in the risk model and their respective sectors. This is also the list of commodities covered by Barclays single-commodity indices.

FIGURE 4

Commodity Types Covered by the POINT Global Risk Model

Energy	Precious Metals	Industrial Metals
Brent Crude	Gold	Aluminum
Gas Oil	Palladium	Copper
Heating Oil	Platinum	Lead
Natural Gas	Silver	Nickel
Unleaded		Tin
WTI Crude		US Copper
		Zinc
Agriculture		**Livestock**
Cocoa	Soybean Meal	Feeder Cattle
Coffee	Soybean Oil	Lean Hogs
Corn	Soybeans	Live Cattle
Cotton	Sugar	
Wheat	Orange Juice	
Kansas Wheat	Rice	
Spring Wheat		

Source: Barclays Research

Commodity indices are essentially a selection of commodity futures contracts with defined weights and a methodology for rolling contracts forward prior to expiration. To maintain exposure to a specific point on a particular commodity forward curve, it is necessary to close out the position in the expiring contract and establish a new position in a new contract for the next delivery month. This process is known as the roll. The roll of commodity futures in our single-commodity benchmark indices takes place from the fifth to the ninth business day of every month, with one-fifth of the total roll amount rolled each day. The roll period is subject to adjustments when market disruptions occur. The use of indices that correspond to a constant maturity on the commodity forward curve provides a relatively stationary time series with a long history, which allows for the construction of risk factors with stable characteristics over time. This becomes especially important for the ability of the model to forecast portfolio risk accurately, and having a long history is also essential in order to have sufficiently long back-testing of the model. The quality of pricing and volume data going into the computation of Barclays indices ensures the reliability and availability of index calculation on a daily basis, which in turn allows for the use of liquid daily data in forecasting the risk of commodity futures at different horizons.

Barclays commodity indices are available in excess return and total return form in USD. An excess return index gives the investor the excess over the return from the collateral used to purchase contracts. We use excess return indices for risk modeling purposes. The return of the index during non-roll days is simply the excess return on a single futures contract, and during the roll period, it is the weighted average return of the expiring and incoming futures contracts. The model is calibrated using a set of excess return indices along the commodity curve ranging from the nearby to the 12-month index. Factors for each commodity type are constructed separately using the set of indices that correspond to the relevant commodity. For certain commodities, the coverage does not extend up to 12 months; therefore, we use whatever is available up to 12 months.

Systematic Risk Factors: Level and Slope

For each commodity type covered by Barclays indices, we construct a level and a slope factor specific to that commodity (slope factor is not defined for orange juice, palladium, platinum, and rice because of liquidity issues). The level factor is defined as the return on the nearby index for each commodity type. The slope factor is defined as the beta-adjusted difference between the returns of the 12-month[2] deferred index and the nearby index.

The level factor aims to capture parallel shifts in an individual commodity curve. We use the nearby index (rather than a deferred maturity) to represent the level factor. This ensures that our level factor measures the risk of futures prices at one of the most liquid points on the curve. To test the explanatory power of the nearby index as a level factor, we proceed as follows: first, we compute the r-squared statistic for each individual index (that corresponds to a specific tenor for a specific commodity) using a model with only this level factor; then we average this statistic across all tenors for a given commodity. We also compare the returns of the level factor with the returns of the first principal component coming out of a PCA model estimated separately for the relevant commodity. Figure 5 shows that the explanatory power of the level factor is generally very high and the level factor is highly correlated to the first principal component across all commodity types.

[2] In certain cases where a 12-month index is not available, we use an alternative index, either 11-month or 8-month, to construct the slope factor.

FIGURE 5

Explanatory Power of the Level Factor

Commodity type	Corr with PC-1	Model R^2	Commodity type	Corr with PC-1	Model R^2
Aluminum	99%	96%	Kansas Wheat	99%	95%
Brent Crude	99%	95%	Lead	99%	94%
Cocoa	99%	97%	Lean Hogs	94%	65%
Coffee	100%	97%	Live Cattle	95%	75%
Copper	100%	97%	Natural Gas	96%	80%
Corn	99%	95%	Nickel	100%	97%
Cotton	98%	89%	Orange Juice	100%	100%
Feeder Cattle	98%	91%	Palladium	100%	100%
Gas Oil	99%	93%	Platinum	100%	100%
Gold	100%	99%	Rice	100%	100%
Heating Oil	97%	87%	Silver	100%	99%
Soybean Meal	97%	89%	Unleaded	98%	91%
Soybean Oil	99%	95%	US Copper	99%	97%
Soybeans	98%	91%	Wheat	99%	95%
Spring Wheat	98%	90%	WTI Crude	98%	88%
Sugar	97%	85%	Zinc	100%	97%
Tin	99%	96%			

Source: Barclays Research

To capture the risk of longer maturity positions and offsetting (spread) positions in a single commodity, we introduce a second factor that represents the slope of the individual commodity curve. These slope factors are defined as the beta-adjusted difference between the returns of the 12-month deferred index and the nearby index.

There are two major reasons behind the choice of 12 months as the tenor to construct the slope factors: First, liquidity tends to deteriorate relatively fast beyond 12 months (for certain commodities, there is substantial liquidity beyond 12 months, but we prefer to keep the definition consistent). Second, this construction helps in the cancellation of the seasonality effect in the slope factor, as the two indices going into the computation belong to the same calendar month at each point in time.

In defining the slope, the beta-adjusting process delivers a factor that is more orthogonal to the level factor, thereby providing a clearer picture of the different risk dimensions. Our procedure is explained with the regression equation below, where r_t^{12M} is the daily return on the 12-month deferred index for the relevant commodity, r_t^{NB} is the corresponding return on the nearby index, β is the beta – sensitivity – of the 12-month index to the nearby index, and ε_t is the residual of the regression:

$$r_t^{12M} = \beta * r_t^{NB} + \varepsilon_t$$

This is a mixed-frequency approach where we use daily data with certain time-weighting to estimate a monthly beta. We also perform adjustments to take into account potential serial correlation in daily commodity returns.

We then divide each side by the beta and rearrange the equation to get the following:

$$\varepsilon_t' = \frac{r_t^{12M}}{\beta} - r_t^{NB}$$

ε_t' in this equation defines the slope factor. Because of the way it is constructed, the slope factor is approximately orthogonal to the level factor, which is simply r_t^{NB}. Defining the factor as a beta-adjusted difference between the 12-month and the nearby index provides a clean representation of the slope effect. If the factor was defined as a simple difference between the two indices, its return would be driven largely by the movements in the nearby index, as that one tends to be more volatile than the corresponding 12-month index. Beta-adjusting provides an adjustment with respect to the volatility difference between the two indices, which can be significant for certain commodity types.

To test the additional explanatory power of the slope factor, we investigate how much it contributes to the average r-squared of the model for each commodity type and analyze the correlation between our slope factors and the second principal component coming out of a PCA approach. Figure 6 shows that the explanatory power of a model with two factors is always above 90%, and comparing with Figure 5, we can see that the contribution coming from the slope factor in this regard varies significantly across different commodity types (1%-27%). Moreover, correlations between slope and PCA factors are again generally high, albeit not as high as in the case of the level factor.

FIGURE 6

Explanatory Power of a Model with Level and Slope Factors

Commodity type	Corr with PC-2	Model R^2	Commodity type	Corr with PC-2	Model R^2
Aluminum	86%	99%	Kansas Wheat	91%	97%
Brent Crude	83%	99%	Lead	87%	98%
Cocoa	95%	100%	Lean Hogs	85%	92%
Coffee	93%	100%	Live Cattle	88%	93%
Copper	90%	100%	Natural Gas	78%	95%
Corn	72%	98%	Nickel	72%	99%
Cotton	87%	96%	Silver	79%	100%
Feeder Cattle	89%	98%	Unleaded	46%	96%
Gas Oil	86%	97%	US Copper	92%	99%
Gold	93%	100%	Wheat	61%	97%
Heating Oil	85%	97%	WTI Crude	89%	96%
Soybean Meal	87%	95%	Zinc	69%	99%
Soybean Oil	78%	99%	Spring Wheat	83%	96%
Soybeans	74%	97%	Sugar	93%	95%
Tin	94%	99%			

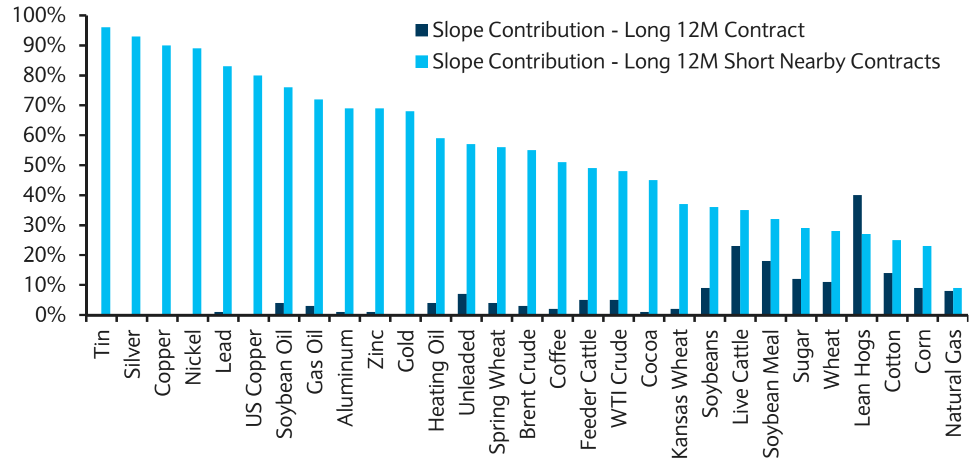
Source: Barclays Research

We tested alternative approaches in model estimation and factor construction. As we have emphasized before, a major goal of this endeavor was to build a model with factors that are intuitive and that have sound economic interpretation. Our methodology allows us to fully control the economic interpretation of the factors. However, we also show that these factors are generally highly correlated to the ones that would have the highest in-sample explanatory power, such as factors that would come out of a principal component analysis.

The risk of long-only portfolios tends to be driven largely by the level factor. However, for portfolios that focus on the long end of the commodity curve and especially for long-short portfolios within a given commodity type, the slope factor becomes more important in explaining the risk. To better understand the relative importance of level and slope factors, we look into the risk contribution coming from these two factors for three simple portfolios for each commodity type: long position in the nearby index, long position in the 12-month deferred index, and a long-short portfolio of the 12-month vs the nearby index. For the nearby index portfolio, all risk is explained by the level factor (as the level factor is defined as the return on the nearby index). Figure 7 shows the risk contribution of the slope factor for the latter two portfolios. For the long-short portfolio, the contribution of the slope factor is typically highly significant, especially for commodities with a relatively flat volatility term structure. For these commodities, being long the 12-month index and short the relevant nearby index almost cancels the exposure to the level factor and, thus, increases the importance of the slope factor in explaining the risk. For the long position in the 12-month index, the risk contribution of the slope factor varies significantly across commodities, and the picture is in line with what we can see when we compare Figures 5 and 6 in terms of the additional explanatory power of the slope factor (eg, lean hogs and live cattle are the commodities with the highest slope factor contribution).

FIGURE 7

Relative Significance of Level and Slope Factors (July 2013)



Source: Barclays Research

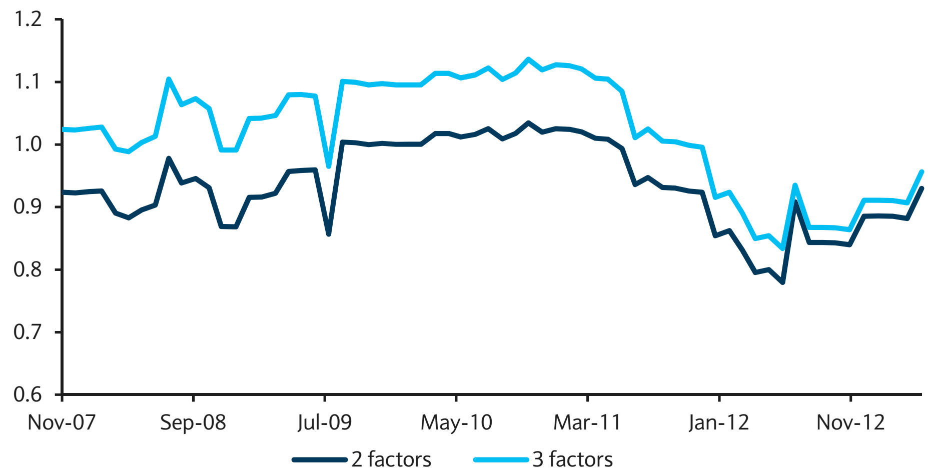
In-sample performance of the model, such as the explanatory power of factors, is an important determinant in model selection, but certainly not the only one that needs to be considered in such an exercise. The ultimate use case of the model is forecasting the portfolio risk; hence, out-of-sample analyses testing the forecasting accuracy of the factors/model should be utilized not only after the model selection process but also directly in the selection of factors.

We investigated the need for a third factor in the model using an out-of-sample testing procedure. One might argue that, for curvature-type trades, a two-factor model with level and slope factors might not capture the risk properly. To test this, we constructed a hypothetical curvature factor and a corresponding hypothetical curvature portfolio for each commodity type and analyzed whether a third factor actually helps in predicting the volatility of such a portfolio. Note that the factor and the portfolio are defined in the same way: a long position in the nearby and 12-month indices and a double short position in the 3-month index. Such a factor would exhibit perfect in-sample performance (explanatory power) by design, but its value in predicting the volatility of such a portfolio is not straightforward. For instance, if the factor does not exhibit stable characteristics over time, its inclusion in the model might bring additional noise into the risk forecasts, rather than improving their accuracy.

We compare the predictive ability of our two-factor model and a hypothetical three-factor model using the aforementioned curvature portfolio. We use an out-of-sample testing approach, which is explained in detail in section 4. We perform this test on a set of commodities[3] where we expect potential improvement from the inclusion of such a factor – eg, natural gas. Figure 8 shows the bias statistics under the two models for this commodity. A value closer to 1 at any point on the graph indicates more accurate forecasting of volatility (on average) over the past two years for that model. We see that a two-factor model performs generally well for such a portfolio and the improvement arising from the addition of the third factor is not clear in an out-of-sample context (both lines are typically within the confidence interval around 1). We had similar observations for other commodity types for which we explored the possibility of a third factor and did not find enough statistical evidence for the inclusion of a third factor in any of those cases.

FIGURE 8

Bias Statistics for a Natural Gas Curvature Portfolio (Long Nearby & 12M, 2x Short the 3M Index) Using a Two-Factor vs a Three-Factor Model



Source: Barclays Research

As mentioned earlier, systematic risk factors are based on Barclays indices in USD. For a futures contract that is denominated in a currency other than USD, the POINT® risk model takes into account the currency exposure by including an additional currency risk factor in the model. These currency factors simply represent the monthly relative change in the FX rate between the two underlying currencies.

Estimating the Risk Factor Loadings

Once the factors are constructed, loadings – sensitivities – to these factors are estimated using a multivariate regression. This is a mixed-frequency approach where we use daily data with certain time-weighting to estimate monthly loadings, ie, betas. We also perform adjustments to take into account potential serial correlation in daily commodity returns.

The following demonstrates the multivariate regression used, where loadings are estimated for each commodity/maturity independently:

$$r_t = \beta_t^L * F_t^L + \beta_t^S * F_t^S + \varepsilon_t$$

r_t is the return on an index (that corresponds to a specific commodity/maturity), F_t^L, F_t^S are, respectively, the relevant level and slope factors, β_t^L, β_t^S are the loadings to these factors, and ε_t is the idiosyncratic return.

[3] This is the set of commodities for which a two-factor model has relatively smaller explanatory power.

Once we have the loadings for each index (Barclays indices across different maturities/commodity types), we assign these loadings to the actual instruments in POINT®, commodity futures contracts, as a function of their commodity type and time to maturity. These security loadings are utilized along with the covariance matrix of factors to forecast the risk of commodity futures portfolios.

As mentioned previously, risk factors are constructed to be approximately orthogonal, which allows for a more robust estimation of loadings in a multivariate context, avoiding potential multicollinearity issues. This approach also provides loadings with intuitive characteristics across the term structure that is illustrated in Figure 9.

Using the above linear factor model, for the nearby index, the set of loadings that would satisfy the above equation is $\beta_t^L = 1 \;\; \beta_t^S = 0,$ because in the case of the nearby index, $r_t = F_t^L = r_t^{NB}$ (in this case, ε_t would also be 0).

Similarly, for the 12-month index, the set of loadings that would satisfy the above equation is $\beta_t^L = \beta_t^S$. Because if we rewrite the above equation, for the 12-month index, by replacing the factors with their respective formulas, we get:

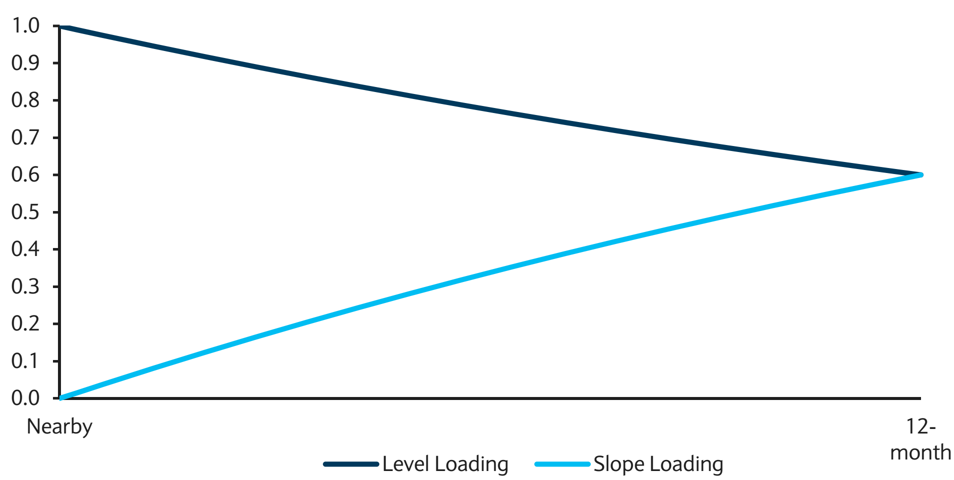
$$r_t^{12M} = \beta_t^L * r_t^{NB} + \beta_t^S * \left(\frac{r_t^{12M}}{\beta} - r_t^{NB}\right) + \varepsilon_t$$

$\beta_t^L = \beta_t^S = \beta$ would satisfy this equation (with ε_t=0). As level and slope factors are orthogonal, β, the sensitivity of the 12-month index to the level factor (nearby index) in a univariate regression, would be the same as β_t^L, the sensitivity of the 12-month index to the level factor in a multivariate regression (that also includes an orthogonal slope factor). Therefore, $\beta_t^L = \beta_t^S$ would satisfy the above equation for the 12-month index.

To sum up, the nearby index has a unit exposure to the level factor and zero exposure to the slope factor, the 12-month index has equal exposures to both factors (the magnitude of this exposure is the sensitivity – beta – of the 12-month index to the nearby index), and the exposures for intermediary maturities tend to be linear combinations of the exposures for the nearby and 12-month indices. Figure 9 shows a representative pattern in the level and slope loadings across the term structure for a given commodity type.

FIGURE 9

Level and Slope Loadings across the Term Structure



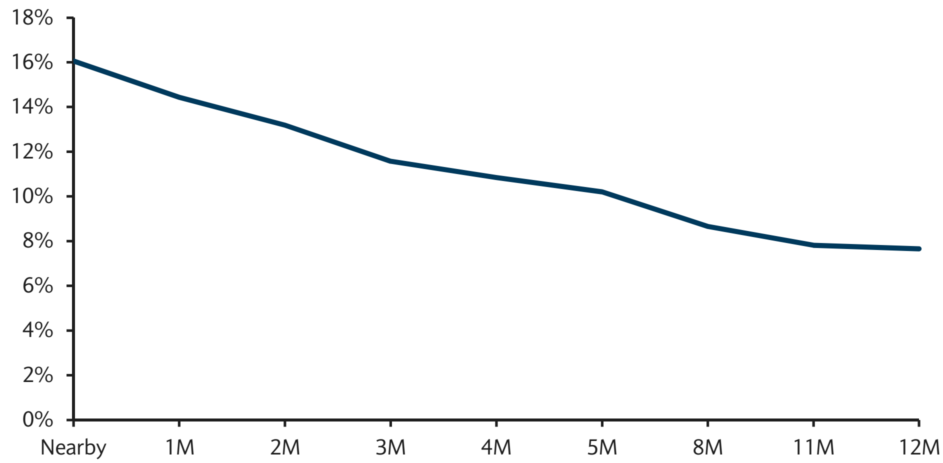
Source: Barclays Research

As we move from the nearby index to the 12-month index, the level loading starts at 1 and decreases monotonically, its pace depending largely on the term structure of volatility, and the slope loading starts at 0 and increases monotonically until the 12-month, where it reaches the same magnitude as the level loading. Note that the actual exposures might vary from this pattern because of limited sample size or other practical considerations.

Decreasing exposure to the level factor as a function of maturity allows us to capture the so-called Samuelson effect (see Samuelson (1965)): shorter maturity contracts exhibiting higher volatility, commonly observed across different commodity types. Figure 10 illustrates this for natural gas, where we see that the monthly volatilities of shorter maturity indices were about double those of longer maturity indices during January 2000-April 2013.

FIGURE 10

Term Structure of Volatility for Natural Gas (Monthly Volatility during Jan00-Apr13)



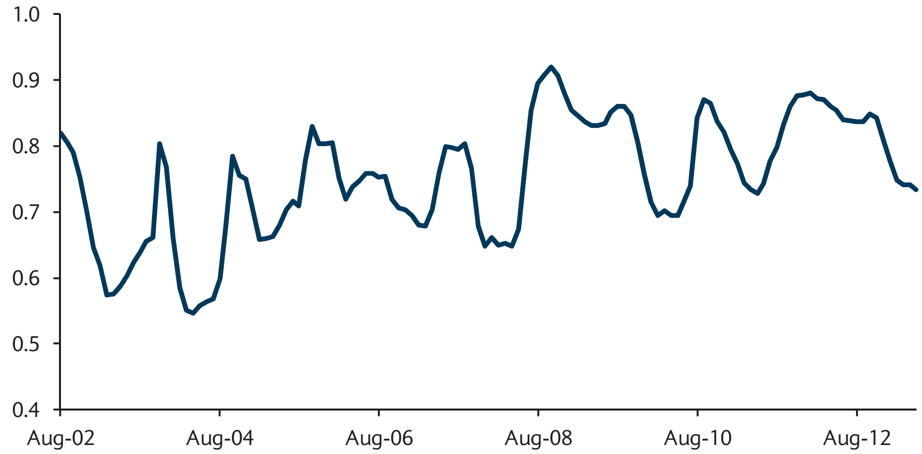
Source: Barclays Research

As mentioned previously, we use a mixed-frequency approach to estimate the factor loadings. This approach uses higher frequency daily data to estimate the monthly loadings. The use of higher frequency data brings two major advantages. Estimates are more responsive to changes in market conditions compared to models that rely solely on monthly data, as roughly 20 new observations are added each month to recalibrate the estimates. Estimates also become more precise as a result of the use of many more data points relative to a model that uses only monthly data. Please refer to Gabudean and Schuehle (2011) for a more detailed discussion on this approach. This methodology was originally applied in POINT® in equity risk modeling, as discussed in Silva, Staal, and Ural (2009).

Factor loadings are recalibrated every month because of the dynamic nature of relationships across the commodity curve, such as the dynamic term structure of volatility. This is especially true during turbulent market conditions. Figure11 illustrates this characteristic for natural gas over the past decade. It shows the ratio of the monthly volatility of the 3-month index to the nearby index volatility over time. We see that the term structure of volatility can vary significantly even over short periods. For instance, around the middle of 2008, the ratio increased from about 0.65 to 0.90 in a few months. The dynamic nature of the relationships necessitates the frequent recalibration of factor loadings to better capture changing risk characteristics.

FIGURE 11

Term Structure of Volatility over Time for Natural Gas



Source: Barclays Research

Once the loadings are estimated, we compute daily residual returns for each index (for each commodity/maturity), the difference between the index return, and its systematic return. These returns form the basis of the idiosyncratic risk forecast for commodity futures. This approach will be discussed in more detail in the next section.

3- Forecasting Risk

The POINT® Global Risk Model covers all major asset classes in a global context. At the heart of the systematic part of the model is a covariance matrix that specifies the relationships between factors from all these asset classes and regions. This matrix is composed of two components, correlations and volatilities, that are estimated separately. This separation adds flexibility to the estimation, where different models/parameters can be used for correlations vs volatilities. The idiosyncratic risk is captured via a different approach and takes into account both volatility of non-systematic returns and significant patterns in residual correlation of different instruments.

POINT® offers users a variety of options in regard to the covariance matrix to be used in the estimation of risk. This includes different time horizons (eg, daily, monthly) and time-weighting of data (eg, unweighted, exponentially-weighted (EWMA) and mixed-frequency (MF)), where different covariance matrices are calibrated to each specific option.

Forecasting Systematic Risk

Because of the size of the covariance matrix, a certain structure is imposed in the estimation of correlations. In this approach, factors are divided into blocks, characterized by economic-based variables such as currency, asset class, or sector. Each block is assigned a small number of core factors, high-level factors that well represent the overall block. Correlations within a block are empirical-based, whereas correlations across blocks are estimated using these core factors. In the case of commodities, blocks are defined by sectors. Sectors are organized as shown in Figure 4.

In this publication, we do not discuss the details of systematic risk forecasting. Please refer to Silva, El Khanjar, and Schuehle (2011) for a more detailed discussion of the covariance matrix in the POINT® Global Risk Model.

Seasonality

An important characteristic of the commodity markets is the existence of seasonal patterns for certain commodities (agriculture, livestock, and some energy commodities) stemming from supply/demand dynamics that depend on the season of the year. These dynamics include both a predictable and an unpredictable component. For instance, there is increased demand for heating-related commodities as winter approaches, which is predictable, yet there is significant uncertainty about actual demand during winter's peak due to uncertainty about weather conditions. Increasing demand before the winter manifests as rising prices, whereas uncertainty in demand during the winter months results in increased price volatility.

Figure 12 shows the average seasonal pattern in prices for an agricultural commodity – the corn nearby index during 1999-2013. The most striking behavior is the large drop in prices during June and July, right before the harvest, which runs from September to November in the US.

FIGURE 12

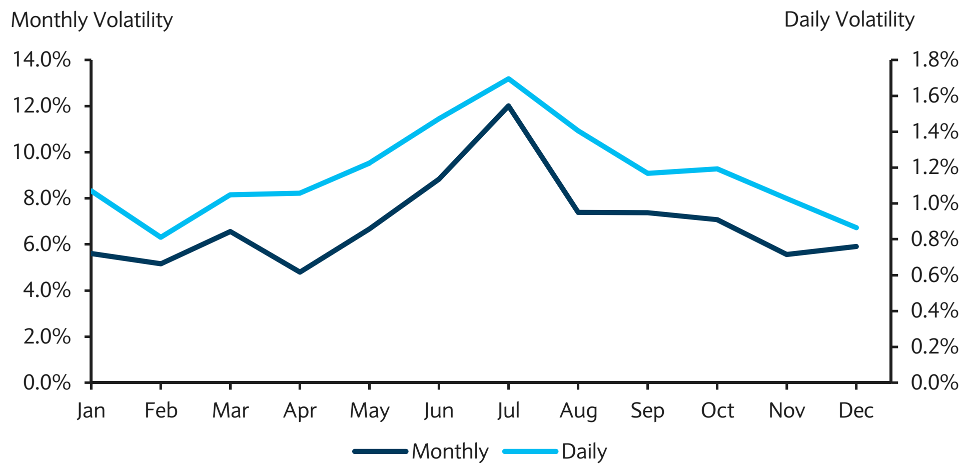
Price Seasonality Pattern for the Corn Nearby Index

Note: Prices rescaled to have an average of 1. Source: Barclays Research

For the purposes of risk modeling, seasonal patterns in returns are more relevant than price patterns, as returns form the basis of the construction of factors. Studies on commodity seasonality suggest that there is less evidence of seasonal patterns in returns compared with price patterns. Our research shows that there are still significant patterns in the dynamics of returns for certain commodities, especially in terms of volatility of returns. Figure 13 shows the volatility of monthly and daily returns for the corn nearby index across various calendar months during 1970-2013. To quantify monthly volatility for any calendar month, we compute the standard deviation of monthly returns across the history for that specific month. To quantify the daily volatility, we first compute the standard deviation of daily returns within each month and then take the median of these numbers across the history for each calendar month.

FIGURE 13

Seasonal Pattern in the Volatility of Returns for the Corn Nearby Index



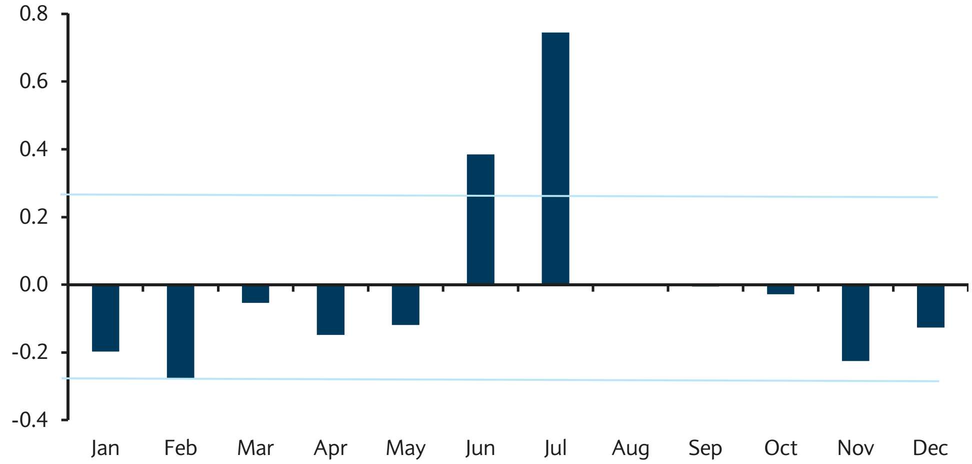
Source: Barclays Research

We see that at both the monthly and the daily horizon, there is increased volatility in returns around the summer, especially for June and July. This is in line with the price pattern we observed in Figure 12, where there are significant drops in prices around these times. The important question from a risk modelling perspective is whether we can capture such seasonal increases in volatility by appropriate time weighting of historical data in our volatility forecasting models or we need to make some seasonal adjustments in our forecasts. We test this using the two time-weighted volatility forecasting models available in POINT® at the monthly horizon– namely, the exponential-weighted moving average (EWMA) and mixed-frequency (MF) models.

Figure 14 illustrates the volatility estimation bias (using EWMA) for the corn level factor – the nearby index – due to seasonality. Every month, we divide the realized return of the factor to its forecasted monthly volatility (using EWMA); we call this the normalized return. We then compute the standard deviation of these normalized returns for each calendar month separately across the history and analyze how different this statistic is from its target value of 1 (see section 4 for a detailed explanation of this test). For instance, for July, the standard deviation of normalized returns (across all July's in history) is 1.75; therefore, Figure 14 shows a bias statistic of 0.75. Note that this differs from a more traditional approach, where the standard deviation is computed over a moving time window or over the whole history. Analyzing the forecasting bias of the volatility estimation model for each calendar month separately allows us to identify the bias introduced by the seasonality effect.

FIGURE 14

Volatility Estimation Bias (using EWMA Model) for Corn Level Factor – the Nearby Index (1973-2013)



Source: Barclays Research

Once we have the bias statistics for each calendar month, we analyze their statistical significance. Because of the limited sample size in the computation of this statistic (sample size is equal to the number of years in history), we compute a 95% confidence interval around the metric (lines in Figure 14) to gauge whether there is enough statistical evidence for the existence of a systematic bias due to seasonality. Figure 14 shows that there are two months where the bias statistic is outside the confidence interval, June and July. Please note that these are also historically the most volatile months, as previously observed in Figure 13.

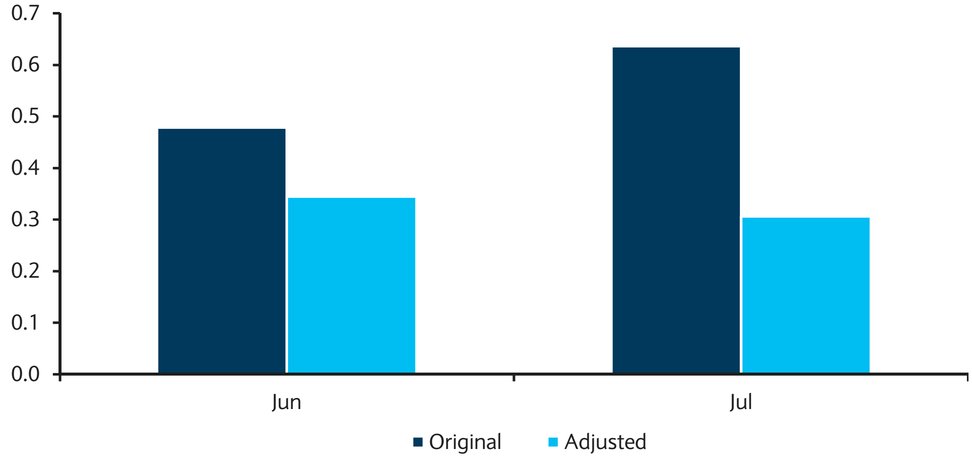
We apply this analysis to all commodities considered to be seasonal – namely, agriculture, livestock, and heating-related energy commodities. We then select the ones that show significant evidence of volatility estimation bias using the above bias statistic (bias statistic that is out of the confidence interval for at least one calendar month). For these commodities, we then use a proprietary algorithm to adjust our volatility forecasts to take into account this seasonal pattern and eliminate the bias. We choose to be conservative; we do the adjustment only for commodities and calendar months with significant evidence for bias and only if the observed pattern is in line with the intuition. As a result, we apply this adjustment only to corn, wheat, soybeans, and heating oil level factors. Note that any seasonality effect for the slope factors is largely eliminated by the fact that these factors are approximately orthogonal to the level factors and are constructed using the 12-month vs the nearby index (both corresponding to the same calendar month). We use this adjustment only for the monthly risk models, as we do not find strong evidence of volatility estimation bias in higher-frequency (weekly or daily) models.

Figure 15 shows how the adjustment factor improves the volatility estimation bias for June and July for the corn nearby index. The adjustment factor at each point in time is computed using only historical data up to that point; it is a function of the volatility estimation bias observed up to that point in time. For the months of June and July, it is essentially a multiplier to the forecasted volatility: greater than 1 if there is historical evidence of underestimation for that calendar month, less than 1 in the case of historical overestimation. We see that after the adjustment, the forecasting bias is reduced for both months, but more so for July, where the initial bias was much higher[4].

[4] Please note that the data period (1983-2013) differs from the previous figure, as some initial history was required to construct the first adjusted volatility estimate.

FIGURE 15

Volatility Estimation Bias (using EWMA) for Corn Level Factor – the Nearby Index – before and after Adjustment for Seasonality (1983-2013)



Source: Barclays Research

Forecasting Idiosyncratic Risk

Even though the term structure of commodities exhibits high correlations, idiosyncratic risk can still be an important component of total risk, especially for portfolios with long-short positions across a commodity curve. The relative significance of idiosyncratic risk depends heavily on the commodity type.

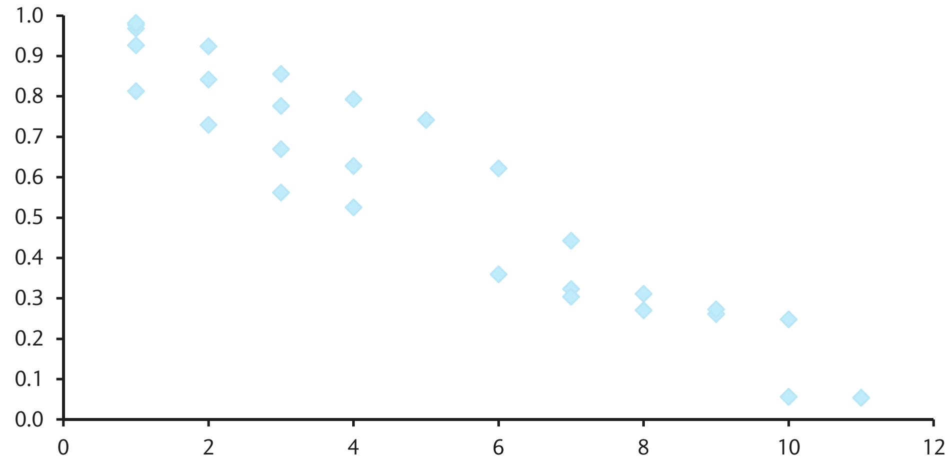
We use daily residual returns from the aforementioned linear factor model with certain time-weighting to estimate the idiosyncratic risk. Similar to what we discussed in the estimation of factor loadings, the use of daily data in this process brings two major advantages: more responsive and precise estimates.

When we analyze correlations between the idiosyncratic returns of different commodity indices, we see that the correlations are relatively low across different commodity types but can be highly significant within a given commodity type.

Figure 16 shows the empirical idiosyncratic correlations for zinc, using data from the whole history (2001-2013). The X-axis represents the difference between two indices in terms of their maturities (in months). Not surprisingly, we see that the correlation decreases as the difference in maturity increases (indices are further apart from each other). We observe such a pattern in a consistent way across different commodity types, but the slope of this relationship can be very different from one commodity type to another.

FIGURE 16

Idiosyncratic Correlations for Zinc as a Function of Maturity Difference (2001-13)



Source: Barclays Research

To take into account such behavior, we fit a linear function to the relationship between difference in maturities and the correlation of idiosyncratic returns:

$$\rho^{i,j} = 1 - \gamma * \Delta^{i,j}$$

where $\rho^{i,j}$ is the correlation between the idiosyncratic returns of two indices i and j, $\Delta^{i,j}$ is the difference between the maturities of these indices (in terms of months), and γ is a parameter that is calibrated specifically to each commodity type using the empirical data illustrated in Figure 16.

To summarize, in forecasting the idiosyncratic risk of commodity futures portfolios, we assume zero correlation of idiosyncratic returns for contracts that belong to different commodity types and a correlation of $\rho^{i,j}$ coming from the above equation for contracts that belong to the same commodity type.

4- Back-Testing the Model

We perform a variety of tests in the development phase of our models to gauge how well the model predicts the risk of different types of portfolios in the relevant market. In this section, we discuss one of those tests and present the results for various portfolios. We first define a set of portfolios to analyze. These portfolios are chosen to cover well the major investment themes/styles for the relevant market and include long-only, long-short, well-diversified, and also specialized portfolios. For each portfolio of interest, we first compute normalized returns by dividing each month's realized return to its estimated volatility at the beginning of the period (includes both systematic and idiosyncratic volatility). This estimation is based on the multi-factor risk model under consideration. Once we have normalized returns, we compute the standard deviation of those returns over the history. If the model performs well, the standard deviation of normalized returns (also called the bias statistic) should be close to 1. To eliminate the effect of large outliers, before we compute the standard deviation, we cap normalized returns at -3 and +3, because in this exercise, the goal is to test forecasting accuracy in terms of volatility, not tail risk. We then compute the confidence interval for this metric in order to quantify its statistical significance. If the standard deviation metric falls above the confidence interval, there is evidence of volatility underestimation (on average) for the relevant time period; if it falls below the confidence interval, it indicates (on average) overestimation. All results presented in this section use the exponentially-weighted (EWMA)[5] monthly model available in POINT®.

Figure 17 presents the bias statistics for long-only single commodity nearby, 3-month, and 12-month indices. All statistics are within the confidence interval, indicating that the model performs well in forecasting the volatility of such indices. Appendix 1 presents the same results for other tenors, where the conclusion stays the same.

FIGURE 17

Bias Statistics for Long-Only Single Commodity Nearby, 3-month, 12-month Indices (2002-13)

Commodity	Nearby	3M	12M	Commodity	Nearby	3M	12M
Aluminum	1.05	1.05	1.06	Natural Gas	0.89	0.93	0.94
Brent Crude	0.94	0.94	0.90	Nickel	0.99	1.00	0.99
Cocoa	1.00	1.00	0.98	Silver	1.07	1.07	1.07
Coffee	0.97	0.96	0.96	Soybean Meal	1.00	1.04	0.96
Copper	0.99	1.01	1.01	Soybean Oil	0.93	0.93	0.92*
Corn	1.07	1.09	1.08	Soybeans	0.99	1.01	0.98*
Cotton	1.03	1.01	1.02	Spring Wheat	1.04	1.05	1.04*
Feeder Cattle	1.12	1.03	0.99*	Sugar	0.97	0.91	0.87
Gas Oil	0.93	0.96	0.99*	Tin	1.07	1.08	0.89
Gold	1.03	1.03	1.03	Unleaded	0.86	0.94	0.88
Heating Oil	0.91	0.98	1.04	US Copper	0.98	1.00	0.99
Kansas Wheat	1.07	1.08	1.05*	Wheat	1.07	1.11	0.95
Lead	1.02	1.03	1.07	WTI Crude	0.95	0.99	1.04
Lean Hogs	0.91	0.97	0.89*	Zinc	1.06	1.06	1.07
Live Cattle	0.96	0.92	0.90*				

Note: * For these commodities, 12-month index was not available and therefore we used the largest tenor available
Source: : Barclays Research

Figure 18 presents the bias statistic for long-only single commodity portfolios (equal weighted across all available tenors). All statistics are again within the confidence interval, indicating that the model performs well in forecasting the volatility of such single-commodity portfolios. Please note that in this case, the ability to capture correlations across indices becomes important.

[5] Conclusions generally stay the same when we use the monthly mixed-frequency (MF) model in POINT as opposed to the EWMA model.

FIGURE 18

Bias Statistics for Long-Only Single Commodity Portfolios across All Tenors (2002-13)

Commodity	Statistic	Commodity	Statistic
Aluminum	1.05	Kansas Wheat	1.03
Brent Crude	0.95	Lead	1.01
Cocoa	0.99	Lean Hogs	1.03
Coffee	0.97	Live Cattle	1.03
Copper	1.01	Natural Gas	0.98
Corn	1.08	Nickel	1.07
Cotton	0.99	Silver	1.01
Feeder Cattle	1.03	Unleaded	1.00
Gas Oil	1.06	US Copper	0.93
Gold	1.03	Wheat	1.00
Heating Oil	0.98	WTI Crude	1.08
Soybean Meal	0.85	Zinc	0.99
Soybean Oil	0.94	Spring Wheat	1.06
Soybeans	1.03	Sugar	1.07
Tin	0.92		

Source: Barclays Research

To further test correlations, we now construct sector portfolios. Figure 19 exhibits the bias statistics for long-only commodity sector portfolios, constructed as equal-weighted averages of nearby indices for all commodity types under each sector, using the sector classification presented before. We see that the model performs very well for such portfolios, with bias statistics very close to 1.

FIGURE 19

Bias Statistics for Sector Nearby Portfolios (2002-13)

Commodity sector	Statistic
Energy	0.97
Agriculture	1.03
Precious metals	0.99
Industrial metals	1.02
Livestock	0.97

Source: Barclays Research

We then move into long-short portfolios. We construct simple long-short portfolios on the same commodity going long a deferred index and short the corresponding nearby index. Figure 20 presents the bias statistics for such portfolios, with 3-month and 12-month indices on the long side (see Appendix 2 for the results on all other tenors available). The bias statistic for about 90% of the portfolios falls within the confidence interval, indicating that the model performs well for the large majority of such portfolios[6]. As mentioned, the slope factor and the idiosyncratic component become much more important for this type of portfolios, as the level effect tends to get cancelled out to some extent, potentially a large extent for certain commodities.

[6] The major reason for the pairs outside the confidence interval tends to be highly instable return distributions over time for such portfolios – eg, cases of sudden regime shifts in volatility.

FIGURE 20

Bias Statistics for Long-Short Single Commodity Portfolios (2002-13)

Commodity	3M-NB	12M-NB	Commodity	3M-NB	12M-NB
Aluminum	0.97	0.87	Natural Gas	0.86	0.89
Brent Crude	0.86	0.86	Nickel	0.84	0.97
Cocoa	0.88	0.96	Silver	0.76	0.84
Coffee	1.00	0.99	Soybean Meal	0.90	1.04
Copper	0.91	0.88	Soybean Oil	0.88	0.94*
Corn	0.92	1.10	Soybeans	0.89	1.00*
Cotton	0.94	1.08	Spring Wheat	0.77	0.88*
Feeder Cattle	1.11	1.19*	Sugar	1.06	1.05
Gas Oil	0.76**	0.83**	Tin	0.83	0.67
Gold	0.74	0.83	Unleaded	0.76**	0.87
Heating Oil	0.80	0.83	US Copper	0.87	0.94
Kansas Wheat	0.71**	0.96*	Wheat	0.86	0.89
Lead	0.76**	0.77**	WTI Crude	0.74**	0.84
Lean Hogs	0.81	0.90*	Zinc	0.93	0.87
Live Cattle	0.94	0.99*			

* For these commodities, 12-month index was not available on the long side; therefore, we used the largest tenor available.

** These are the portfolios for which the bias statistic is outside the confidence interval.

Source: Barclays Research

Following up on our discussion in section 2 about the ability of the model to forecast the risk of curvature portfolios, Figure 21 presents the bias statistics for single-commodity curvature portfolios – namely, long the nearby and the 12-month and double short the 3-month indices. All bias statistics are within the confidence interval, supporting our decision not to include a third factor in the risk model.

FIGURE 21

Bias Statistics for Single Commodity Curvature Portfolios (2002-13)

Commodity type	Statistic	Commodity type	Statistic
Aluminum	0.87	Kansas Wheat	0.86*
Brent Crude	0.86	Lead	0.85
Cocoa	0.99	Lean Hogs	0.95*
Coffee	1.00	Live Cattle	0.92*
Copper	0.97	Natural Gas	1.04
Corn	1.12	Nickel	0.86
Cotton	0.92	Silver	0.90
Feeder Cattle	0.91*	Unleaded	0.89
Gas Oil	0.88*	US Copper	1.05
Gold	0.84	Wheat	0.94
Heating Oil	1.20	WTI Crude	1.06
Soybean Meal	1.20	Zinc	0.82
Soybean Oil	0.90*	Spring Wheat	0.86*
Soybeans	1.04*	Sugar	0.87
Tin	1.02		

Note: * For these commodities, 12-month was not available on the long side; therefore, we used the largest tenor available

Source: Barclays Research

Finally, Figure 22 presents the bias statistic for certain well-known cross-commodity spread trades such as crack spreads in the oil industry (ie, crude oil vs petroleum products extracted from crude oil). These are long-short portfolios between commodity types that exhibit similar characteristics or are naturally related to each other (for instance, one commodity can be used to make the other or one commodity can be a replacement for the other). We see that the model performs well for such spread trades, with all statistics within the confidence interval. For this exercise, we use nearby indices on these commodity types.

FIGURE 22

Bias Statistics for Cross-Commodity Spread Portfolios (2002-13)

Spread trade	Statistic
Heating oil <-> Brent	0.84
Heating oil <->WTI	0.92
Brent <-> WTI	0.85
Live cattle <-> Feeder cattle	1.07
Aluminum <-> Copper	1.03
Corn <-> Wheat	1.00
Wheat <-> Kansas wheat	0.91

Source: Barclays Research

5- POINT® Risk Report

In this section, we illustrate certain parts of the risk report in POINT® using a commodity futures portfolio. We first discuss some of the major options available to users in running the risk report and then illustrate certain sections of a particular risk report. We focus on volatility estimates; however, POINT® also provides tail risk analysis. We use a Barclays strategy index, the Barclays DJ-UBS CI Pure Beta Index, as our portfolio. Standard commodity benchmarks provide exposure to the front part of the futures curves. Pure Beta indices are designed to provide a more representative measure of commodity market returns while retaining the tradability of standard commodity benchmarks. They achieve this by using a multi-step selection process to assess the relevance of different futures contracts and to select a single tenor for each commodity. Please refer to Williams and Barreto (2010) for a more detailed description of these indices.

Here are the list of parameters used the run the report:

Portfolio: Barclays DJ-UBS CI Pure Beta Index

Benchmark: Cash

Report as-of-Date: 8/12/2013

Covariance Matrix: Time-Weighted (EWMA)

Security Partition: Commodity Sectors (a custom partition based on the “Class3” attribute)

Base Currency: USD

There are various options in the risk report that allow for substantial customization; in this section we discuss only certain major options. We choose cash as our benchmark, as we are interested in a forecast for the volatility of the portfolio on a standalone basis. The time-weighted option in the report utilizes monthly data with an exponential weighting scheme in estimating the covariance matrix, as briefly mentioned in section 3. A custom security partition is constructed for this exercise, using the commodities sector classification illustrated in Figure 4.

Figure 23 exhibits the overall volatility forecast for the portfolio, along with its two major components, systematic and idiosyncratic volatility. Because there is no benchmark for the portfolio, tracking error volatility (TEV) essentially means volatility. Unsurprisingly, the idiosyncratic component is much smaller given that the systematic part of the model tends to explain a very large component of overall risk for most commodity contracts and the idiosyncratic risk is largely diversified away by the existence of various commodity types within the portfolio.

FIGURE 23

Summary Statistics for the Portfolio Volatility (in bp/month)

TEV Summary	
Total TEV	388.3
Systematic TEV	386.9
Idiosyncratic TEV	32.9

Source: POINT

Figure 23 gives us a glimpse into the overall risk of the portfolio. However, the portfolio manager would want to know in more detail what the sources of this risk are. Risk can be broken down along various dimensions; eg, across security groups. Figure 24 presents the risk breakdown across different commodity sectors.

Contribution to TEV (CTEV) provides the contribution of a given security bucket to the overall volatility of the portfolio, taking into account the correlations across buckets. It allows us to understand the impact of the different positions on the portfolio's total risk and to detect potential sources of diversification among these different positions in the portfolio. The total CTEV of a sector is further broken down into a systematic and idiosyncratic CTEV, where the idiosyncratic contributions are minimal, in line with Figure 23. The sector with the largest contribution to overall volatility is energy (130.6 bp/month), mainly because of the relatively large weight of the sector within the portfolio. It is interesting to see that livestock has a negligible total contribution – a function of both low (and slightly negative) correlations between this sector and other sectors and its relatively small weight in the portfolio.

FIGURE 24

Partial View from the Security Partition Report (in bp/month)

Partition Bucket	Contribution to TEV (CTEV)		
	Systematic	Idiosyncratic	Total
Total	385.5	2.8	388.3
Energy	128.7	1.9	130.6
Industrial Metals	86.1	0.0	86.2
Precious Metals	58.3	0.0	58.3
Agriculture	113.4	0.9	114.2
Livestock	-1.0	0.0	-1.0

Source: POINT

Figure 25 presents the correlations between security partition buckets (sectors). These correlations are a function of the composition of sector buckets in the portfolio and the covariance matrix of commodity factors. Correlations are generally positive, as expected, except for those between livestock and other sectors. The highest correlation is between the two metal sectors – a 50% correlation between industrial and precious metals.

FIGURE 25

Partial View from the Security Partition Correlation Report

Security Partition Correlation					
Partition Bucket	Correlations				
Systematic TEV	1	2	3	4	5
1 Energy	1.00	0.28	0.42	0.29	0.01
2 Agriculture	0.28	1.00	0.39	0.32	-0.15
3 Industrial Metals	0.42	0.39	1.00	0.50	-0.05
4 Precious Metals	0.29	0.32	0.50	1.00	-0.15
5 Livestock	0.01	-0.15	-0.05	-0.15	1.00

Source: POINT

So far we have discussed breakdown of risk in terms of security buckets. The POINT® risk report also provides a breakdown in terms of factors and factor partitions. Figure 26 illustrates a partial view from the factor exposure report in POINT® (for simplicity, only certain factors are shown here). This report shows a variety of details with respect to a portfolio's individual factor exposures. As Figure 26 suggests, the factor list is composed of level and slope factors per commodity type.

Portfolio exposure shows the loading of the portfolio to a given risk factor, taking into account the weight of securities corresponding to the relevant factor. The sum of exposures to all level factors is 0.89 (less than 1, not shown in the figure), in line with the fact that Pure Beta indices do not necessarily invest in nearby contracts. Factor volatility is the forecasted volatility of the factor for the next one month, as a function of the covariance matrix calibration chosen (in this example, time-weighted). As we can see, level factors are more volatile than slope factors, with the difference sometimes very large (eg, gold). It is also interesting to see the large variation across the volatilities of slope factors (eg, 12bp for gold vs 455bp for wheat). Metals that tend to have a relatively flat term structure are among the factors with the smallest slope volatility.

If we interpret the factor volatility as a typical monthly move in the factor, columns 5 and 6 show the potential impact of such a move on the return of our portfolio. For instance, a typical move up (966 bp/month) in the corn level factor (which can be interpreted as a movement in the level of corn futures curve), when considered in isolation, will deliver a positive return of 58bp for the portfolio. A more interesting metric might be the correlated number in the figure – the same return impact, but assuming that all other factors move accordingly, as a function of correlations across factors. In the scenario under analysis, a movement in the corn level factor will involve a movement in other factors across commodities, with the largest effect likely on other factors within the same sector, as well as related commodities (eg, corn linked to lean hogs). The correlated impact of an upward change in the same factor is much larger, at 260bp, largely because of positive correlations between this factor and some other level factors in the portfolio. From a contribution to TEV perspective, the WTI crude level factor is the largest contributor to overall risk. Not surprisingly, slope contributions are much smaller, as the portfolio is composed of long-only positions.

FIGURE 26

Partial View from the Factor Exposure Report (bp/month)

Factor name	Sensitivity / Exposure	Portfolio Exposure	Factor Volatility	TE impact of an isolated 1 std. dev. up change	TE impact of a correlated 1 std. dev. up change	Contribution to TEV
USD Commodities Corn Level	Empirical Beta	0.060	966.23	57.96	259.73	38.77
USD Commodities Gold Level	Empirical Beta	0.103	604.65	62.47	245.37	39.48
USD Commodities Heating Oil Level	Empirical Beta	0.041	619.54	25.53	262.94	17.29
USD Commodities Live Cattle Level	Empirical Beta	0.028	292.85	8.13	-35.85	-0.75
USD Commodities Natural Gas Level	Empirical Beta	0.104	1,004.92	104.71	114.12	30.77
USD Commodities Soybeans Level	Empirical Beta	0.057	716.81	41.07	252.93	26.76
USD Commodities US Copper Level	Empirical Beta	0.075	704.05	52.78	280.37	38.11
USD Commodities Wheat Level	Empirical Beta	0.034	874.45	29.39	230.68	17.46
USD Commodities WTI Crude Level	Empirical Beta	0.117	744.16	86.91	272.82	61.06
USD Commodities Corn Slope	Empirical Beta	0.029	432.99	12.34	-53.05	-1.69
USD Commodities Gold Slope	Empirical Beta	0.034	12.82	0.43	-59.88	-0.07
USD Commodities Heating Oil Slope	Empirical Beta	0.012	190.49	2.33	47.16	0.28
USD Commodities Live Cattle Slope	Empirical Beta	0.014	230.48	3.19	11.52	0.09
USD Commodities Natural Gas Slope	Empirical Beta	0.041	451.68	18.39	34.90	1.65
USD Commodities Soybeans Slope	Empirical Beta	0.019	339.93	6.51	-76.25	-1.28
USD Commodities US Copper Slope	Empirical Beta	0.022	62.93	1.39	33.75	0.12
USD Commodities Wheat Slope	Empirical Beta	0.009	455.24	3.93	4.27	0.04
USD Commodities WTI Crude Slope	Empirical Beta	0.046	252.80	11.64	-19.93	-0.60

Source: POINT

Finally, we present some analysis at the individual security level. Figure 27 shows a partial view from the issue report in POINT, with systematic and idiosyncratic risk of individual securities in an isolated sense. Natural gas is the contract with the largest idiosyncratic risk. However, even in that case, the systematic component is, unsurprisingly, significantly larger (about four times the idiosyncratic component). Idiosyncratic risk in the portfolio tends to diversify away quickly as it is composed of futures contracts from different commodity types.

FIGURE 27

Partial View from the Issue Report (bp/month)

Identifier	Description	Maturity	Systematic TEV	Idiosyncratic TEV
HGZ13:CMX	High Grade Copper (Grade 1)	12/27/2013	52.92	0.91
SIU13:CMX	Silver 5000	9/26/2013	33.30	0.05
BOZ13:CBT	Soybean Oil	12/13/2013	17.05	1.66
NGF14:NYM	Natural Gas	12/27/2013	103.02	25.69
LCZ13:CME	Live Cattle	12/31/2013	8.63	3.21
LHG14:CME	Lean Hogs	2/14/2014	7.41	1.00
RBZ13:NYM	Unleaded Gasoline	11/29/2013	28.24	3.14
CZ13:CBT	Corn	12/13/2013	54.83	13.48

Source: POINT

References

S. Cooper, S. Luo, K. Norrish, and M. Corsi (2013), The Commodity Investor - Signals or Noise?, Barclays, 15 February 2013.

R. Gabudean and N. Schuehle (2011), Volatility Forecasting: A Unified Approach to Building, Estimating, and Testing Models, Barclays Capital, November 2011.

P. A. Samuelson (1965), Proof that properly anticipated prices fluctuate randomly, Industrial Management Review, 1965 Spring.

A. Silva, A. El Khanjar, N. Schuehle (2011), Covariance Matrix in the GRM: A Note on Changes in the Methodology, Barclays Capital, May 2011.

A. B. Silva, A.D. Staal, and C. Ural (2009), The US Equity Risk Model, Barclays Capital, July 2009.

C. Ural (2010), Linear Factor Models: Structure, Estimation, and Factor Selection, Quantitative Portfolio Management Conference, Barclays Capital, April 2010.

J. Williams and M. Barreto (2010), Pure Beta Series-2: Replicating the Front Year Commodity Futures Returns, Barclays Capital, December 2010.

J. Williams, Y. Tian, and M. B. Rivera (2011), Barclays Capital Commodity index (BCI), Barclays Capital, March 2011.

APPENDIX 1: LONG-ONLY SINGLE COMMODITY PORTFOLIOS: VOLATILITY ESTIMATION BIAS STATISTIC

	Nearby	1M	2M	3M	4M	5M	8M	11M	12M
Aluminum	1.05	1.05	1.04	1.05	1.05	1.05	1.06	1.07	1.06
Brent Crude	0.94	0.94	0.94	0.94	0.94	0.94	0.93	0.90	0.90
Cocoa	1.00	1.01	1.00	1.00	1.00	1.00	0.99	0.97	0.98
Coffee	0.97	0.97	0.97	0.96	0.97	0.98	0.97	0.97	0.96
Copper	0.99	1.00	1.00	1.01	1.02	1.01	1.01	1.02	1.01
Corn	1.07	1.07	1.09	1.09	1.10	1.11	1.12	1.10	1.08
Cotton	1.03	1.03	1.01	1.01	1.00	0.98	0.99	0.99	1.02
Feeder Cattle	1.12	1.10	1.07	1.03	1.03	0.99	-	-	-
Gas Oil	0.93	0.94	0.95	0.96	0.97	0.97	0.99	-	-
Gold	1.03	1.03	1.03	1.03	1.03	1.03	1.03	1.03	1.03
Heating Oil	0.91	0.94	0.96	0.98	0.99	1.00	1.02	1.04	1.04
Kansas Wheat	1.07	1.07	1.07	1.08	1.09	1.07	1.05	-	-
Lead	1.02	1.03	1.03	1.03	1.03	1.03	1.03	1.06	1.07
Lean Hogs	0.91	0.95	0.94	0.97	0.91	0.86	0.89	-	-
Live Cattle	0.96	0.96	0.97	0.92	0.92	0.89	0.90	-	-
Natural Gas	0.89	0.91	0.93	0.93	0.94	0.94	0.91	0.94	0.94
Nickel	0.99	0.99	1.00	1.00	1.00	1.00	1.00	0.98	0.99
Silver	1.07	1.07	1.07	1.07	1.07	1.07	1.07	1.07	1.07
Soybean Meal	1.00	1.02	1.03	1.04	1.03	1.04	1.05	0.99	0.96
Soybean Oil	0.93	0.93	0.93	0.93	0.94	0.94	0.93	0.92	-
Soybeans	0.99	1.00	1.00	1.01	1.01	1.01	1.01	0.98	-
Spring Wheat	1.04	1.04	1.05	1.05	1.04	1.04	-	-	-
Sugar	0.97	0.95	0.94	0.91	0.93	0.91	0.90	0.88	0.87
Tin	1.07	-	-	1.08	1.08	1.08	1.08	1.07	0.89
Unleaded	0.86	0.89	0.93	0.94	0.95	0.96	0.93	0.88	0.88
US Copper	0.98	0.99	1.00	1.00	1.01	1.01	1.01	1.00	0.99
Wheat	1.07	1.08	1.10	1.11	1.13	1.13	1.14	1.15	0.95
WTI Crude	0.95	0.96	0.98	0.99	1.00	1.01	1.02	1.03	1.04
Zinc	1.06	1.06	1.07	1.06	1.06	1.06	1.05	1.08	1.07

Source: Barclays Research

APPENDIX 2: LONG-SHORT SINGLE COMMODITY PORTFOLIOS: VOLATILITY ESTIMATION BIAS STATISTIC

	1M-NB	2M-NB	3M-NB	4M-NB	5M-NB	8M-NB	11M-NB	12M-NB
Aluminum	0.93	0.97	0.97	0.97	0.96	0.91	0.83	0.87
Brent Crude	0.80	0.84	0.87	0.86	0.86	0.89	0.86	0.86
Cocoa	0.82	0.90	0.88	0.91	0.93	0.92	0.94	0.96
Coffee	0.84	0.92	1.00	0.96	0.94	0.96	0.98	0.99
Copper	0.86	0.89	0.91	0.90	0.90	0.86	0.83	0.88
Corn	0.81	0.92	0.92	0.98	0.96	1.02	1.01	1.10
Cotton	0.84	0.93	0.94	0.99	1.03	1.07	1.07	1.08
Feeder Cattle	0.95	1.07	1.11	1.16	1.19*	-	-	-
Gas Oil	0.77*	0.77*	0.76*	0.78	0.79*	0.83*	-	-
Gold	0.76*	0.75	0.74	0.79	0.82	0.84	0.84	0.83
Heating Oil	0.85	0.82	0.80	0.79	0.79	0.80	0.82	0.83
Kansas Wheat	0.68	0.76	0.71*	0.80	0.86	0.96	-	-
Lead	0.71*	0.75*	0.76*	0.79	0.79	0.74*	0.76*	0.77*
Lean Hogs	0.86	0.86	0.81	0.80	0.86	0.90	-	-
Live Cattle	0.87	0.88	0.94	0.94	0.96	0.99	-	-
Natural Gas	0.78	0.88	0.86	0.83	0.82	0.89	0.89	0.89
Nickel	0.61*	0.77*	0.84	0.85	0.82	0.86	0.95	0.97
Silver	0.80	0.80	0.76	0.78	0.80	0.79	0.83	0.84
Soybean Meal	0.77	0.79	0.90	0.92	0.93	0.99	1.04	1.04
Soybean Oil	0.82	0.85	0.88	0.85	0.89	1.05	0.83	0.94
Soybeans	0.71	0.85	0.89	0.98	0.99	0.96	1.00	-
Spring Wheat	0.94	0.76	0.77	0.88	0.88	-	-	-
Sugar	0.93	1.08	1.06	1.03	1.01	1.01	1.03	1.05
Tin	-	-	0.83	0.89	0.95	1.04	1.09	0.67
Unleaded	0.78*	0.76*	0.76*	0.76	0.76*	0.73*	0.87	0.87
US Copper	0.93	0.97	0.87	0.85	0.88	0.94	0.95	0.94
Wheat	0.79	0.80	0.86	0.87	0.98	0.98	1.14	0.89
WTI Crude	0.71*	0.73*	0.74*	0.76	0.77*	0.82	0.84	0.84
Zinc	0.95	0.97	0.93	0.95	0.95	0.87	0.88	0.87

* These are the portfolios, for which the bias statistic is outside the confidence interval.

Source: Barclays Research

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