Model Insight

The Barra Commodity Model (COM2)

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About This Document

This document describes the new and enhanced Barra Commodity Model, COM2, and provides a comparison with the model it replaces, COM1. COM1, available in the Barra Integrated Model (BIM) since 2002, allowed clients to monitor the risk of portfolios with spot commodities or commodity futures positions, but its main focus was to cover commodities as an asset class for asset allocation purposes. The introduction of COM2 is driven by the desire to expand the set of covered commodities and to provide more accurate risk estimates along the term structure. Unlike COM1, which was based on monthly data corresponding to the S&P GCSCI® commodity indices, the new model uses *daily* data for all traded maturities along the futures curve.

The main enhancements delivered by COM2 are:

- asset coverage expanded from 24 to 34 commodities
- a more granular risk model with one, two, or three sources of risk, depending on commodity
- introduction of Rolling Maturity Futures (RMF) – a daily time series that serves as the model estimation universe
- improved risk forecasts along the commodity term structure
- specific risk forecasts through a specific risk model for RMFs and individual futures contracts

The format of the paper is the following: after this section, Chapter 1 provides a primer on commodity investing; Chapter 2 introduces the COM2 estimation universe represented by the Rolling Maturity Futures; Chapter 4 explains COM2 factors and the calculation of factor exposures; Chapter 4 focuses on factor return estimation via cross-sectional regressions; Chapter 5 describes factor risk and specific risk models; Chapter 6 explains how COM2 is integrated in BIM301; and Chapter 7 presents a number of tests that help us assess the model's forecasting performance. Summary tables can be found in Appendix A, while Appendix B and C have details on RMF construction and calculation, respectively. Appendix D explains the methodology used to add new exposures if the estimation universe were to expand.

1 A Primer on Commodity Investing

1.1 A Brief History

The past decade has seen an astounding growth in investment demand for commodities. The major market correction experienced in 2008 did not seem to dampen investors' appetite for commodity investing. By some estimates(Barclays Capital, April 2010), total commodity assets under management were USD 277.5 billion at the end of 2009, with record yearly inflows of USD 71.8 billion.

This increased interest is driven by the perception that commodities provide an alternative source of return that is weakly correlated with stocks and bonds, thus providing diversification within a multi-asset class portfolio.

Generally, stocks and bonds are negatively correlated with inflation, which makes their returns vulnerable to inflation. Commodities, however, are positively correlated with inflation, unexpected inflation, and changes in the inflation rate(Bodie, 1983). These characteristics make commodities attractive to investors during periods of high inflation.

An obvious way to invest in commodities is to buy and hold the physical good. Except for precious metals, however, it is expensive, and in some cases impossible to store these assets.

Historically, the preferred strategy of obtaining commodity exposure has been through indirect investment in the equity of commodity producers. This, however, leaves investors exposed to the specific risk of each company, such as its hedging policy and capital structure.

The desire for direct commodity investment led to the creation of a number of passive, long-only, investable commodity indices in the 1990s. In addition to accessing these asset class returns, institutional investors can use these indices as a source of information on commodity market trends, as benchmarks for evaluation of active funds and for developing asset allocation strategies.

In the 2000s, exchange traded products allowed retail investors to participate in the commodity investment boom. The majority of commodity-linked exchange traded funds and notes track an existing commodity index, while a few invest in physical precious metals. On the institutional side, structured products like medium-term notes gained popularity.

1.2 Spot Commodities

On a number of levels, physical commodities are different from financial assets like equity and foreign exchange. Since it takes longer for the production side to catch up with short-term supply or demand shocks, price movement can be dramatic. Storage can play a critical role in dampening volatility and enabling price discovery, but storability varies wildly across different commodities: relatively cheap for precious metals, expensive for natural gas and agricultural commodities, impossible for livestock and electricity. Price seasonality is another defining characteristic of many commodities, since it is related to the production and demand cycles and storability.

The inherent volatility associated with the above characteristics has served as a deterrent to investing, but it has also been a source of alpha with low correlation to traditional asset classes.

1.3 Commodity Futures

A commodity futures contract is an agreement to buy or sell an asset at a certain future time for a specified price -- the futures price. At inception, the contract value is zero and no cash changes hands. Gains and losses are settled on a daily basis through a margin account, effectively resetting the contract value to zero. While futures contracts may be held to expiration (requiring receipt/delivery of the underlying commodity), they are most often used as financial contracts that provide commodity exposure without the infrastructure necessary for physical delivery. Commodity futures are thus increasingly used by asset managers to manage commodity risk in institutional portfolios.

A futures contract locks the terms of trade for a future transaction. Therefore the futures price embeds expectations of the future spot price. If price expectations increase relative to the current spot price, so will the futures price, and vice versa. As a result, a long position in a futures contract benefits (or loses) when the spot price at maturity ends up higher (or lower) than expected at inception.

If the current futures price is consistently set below the expected futures spot price, then the long position on average earns money, while the short position loses money. The theory by (Keynes, 1930) and (Hicks, 1939) on normal backwardation[1] postulated that this is indeed the case, and a risk premium should accrue to the buyers of futures contracts. They explained the effect with the discount that hedgers/producers, who are short the commodity, need to offer speculators in order to induce them to assume the price risk by entering the long position.

There have been numerous empirical studies of the risk premium in commodity futures markets and a number of them have confirmed its existence. This effect has been an important source of return for long-only commodity investing using commodity indices, but its effectiveness as a source of alpha has been seriously questioned in the past few years.

1.4 Commodity Indices

An unleveraged commodity index represents the returns that would be earned by holding only long positions in commodity futures contracts. As the futures contracts approach expiration, positions will be rolled in a predefined manner into futures contracts with a more distant maturity.

To be unleveraged, the position must be fully collateralized with Treasury bills. For example, to enter a long position in crude oil futures contract with futures price of USD 70, an investor will allocate USD 70,000 from his portfolio and purchase T-bills as collateral.

A typical commodity index is a weighted long portfolio of futures contracts on a number of commodities. Different indices cover different commodities with different weighting schemes.

1.4.1 S&P GSCI

The index was originally developed by Goldman Sachs. In 2007, ownership transferred to Standard & Poor’s, who currently own and publish it. It is by far the largest commodity index in terms of funds tracking its performance.

The index currently covers 24 commodities from five commodity sectors -- energy products, industrial metals, agricultural products, livestock products and precious metals. Each commodity index passively invests in the front end of the future curve; physical delivery of the commodity is avoided by switching from one contract to the next during a 5-day period on a monthly basis.

[1] Normal backwardation is different from a market that is currently in backwardation. A futures price curve is said to be in backwardation when prices decrease with increasing maturity; it is said to be in contango when prices increase with increasing maturity.

The S&P GSCI is calculated primarily on a world production-weighted basis (dollar adjusted) with weights for each commodity that are based on the last five years of available data. The index contains a much higher exposure to energy than other commodity price indices.

1.4.2 J.P. Morgan Commodity Curve Index (JPMCCI)

Launched in 2007, JPMCCI currently tracks the performance of 35 commodity markets. By investing along the entire length of the futures curve in proportion to its open interest, JPMCCI avoids the front-end bias of traditional indices.

1.4.3 Dow Jones-UBS Commodity Index (DJ-UBSCI)

DJ-UBSCI is composed of futures contracts on 19 physical commodities and was launched on July 14, 1998.

To determine its component weightings, the DJ-UBSCI relies primarily on liquidity data, or the relative amount of trading activity of a particular commodity. The index also relies to a lesser extent on dollar-adjusted production data.

To help ensure diversified commodity exposure, the DJ-UBSCI relies on several diversification rules:

- No related group of commodities (e.g., energy, precious metals, livestock and grains) may constitute more than 33% of the index as of the annual re-weightings of the components.
- No single commodity may constitute less than 2% or more than 15% of the index.

1.4.4 Other Commodity Indices

Other commodity indices include the Thomson Reuters/Jefferies CRB Index (TR/J CRB) composed of 28 commodities, the Rogers International Commodity Index (RICI) tracking 36 markets, and the Deutsche Bank Liquid Commodity Index (DBLCI) covering only six commodities.

1.5 Exchange-Traded Products

Exchange Traded Products is a generic term covering Exchange Traded Funds (ETF), Exchange Traded Notes (ETN), and Exchange Traded Commodities (ETC).

Commodity ETFs are investment products tracking an individual commodity or an index such as any of the S&P GSCI indices. ETFs trade like stocks on an exchange. ETNs are debt instruments issued by banks that promise to pay an index return, minus fees and taxes; unlike ETFs, investors are exposed to credit risk. ETNs also have different tax treatment. ETCs are open-ended asset-backed securities and can be regarded as secured, undated, zero-coupon notes that trade through an open market-maker platform.

Launched less than ten years ago, ETPs have quickly become the most popular way to invest in commodities, benefiting from increased liquidity and the ability to take short positions. Assets under management have experienced an unprecedented growth to more than USD 50 billion.

While the majority of ETPs use commodity futures or indices as underlying, there are several precious metals ETFs that are backed by physical holdings. The largest ones are gold ETFs, like the SPDR Gold Trust that is backed by more than one thousand tons of gold.

1.6 Structured Products

Structured notes are fixed income-like securities in which the payoff is linked to the performance of an underlying asset or derivative, providing investors with a stream of cash flows and highly customizable features, like principal-protection or leveraged exposure. When it comes to commodities, such notes often have the coupon or redemption benchmarked to a commodity index, a basket of commodity prices, or a single commodity price.

Issued mainly by investment banks, structured notes are highly customizable and can achieve targeted exposure often required by more sophisticated investors.

2 The Estimation Universe: Rolling Maturity Futures

Historically, excess return commodity indices like GSCI have represented investable portfolios in the front part of a commodity curve. Rolling Maturity Futures (RMF) are dynamic portfolios of two futures contracts that are a natural generalization of GSCI indices for expiries further along the curve. Their definition is similar to that of constant maturity futures, a construct that is often used in commodity and fixed income markets to generate time series from contracts that, because of their expiration, lack long time series. It is important to realize that the investment return using an RMF strategy could be very different from the returns obtained by investing directly in the physical commodity, or the returns one would expect to achieve through a simple view on the expected behavior of commodity prices. For instance, investing in the first oil RMF would have returned 2.6% over 2009, while the oil price level rose 71.3%. On the other hand, investing in the oil RMF with a maturity close to six months would have returned 30.2%.

2.1 A Simple Example

In order to illustrate the sources of commodity investment return, consider a futures contract that delivers in March, May, July, September and December. On February 1, 2010, a commodity investor allocates USD 100 to a fully collateralized investment in commodity futures and enters a long position in the second nearby May 2010 contract at USD 100. In two months, he “rolls the contract” by closing the position in the expiring May contract at USD 120 and simultaneously enters a long position in the second nearby July contract at USD 110. In another two months, on June 1, 2010, the position is closed at USD 99. Assume that the spot commodity price is equal to the first nearby contract price and that there are no storage or transaction costs. How would this investment compare with simply buying, storing and selling the spot commodity?

Table 2-1. A Simple Example of Spot and Excess Return.

Date	March 2010	May 2010	July 2010	First Nearby	Spot Price	Excess Return	Capital
Feb 1, 2010	USD110	USD100	USD90	March 2010	USD110		USD100
Apr 1, 2010	NA	USD120	USD110	May 2010	USD120	20%	USD120
Jun 1, 2010	NA	NA	USD99	July 2010	USD99	-10%	USD108
					-10%		8%

The investment in futures yields 20% return on April 1, and another -10% on June 1 for an overall return of 8%. The spot commodity investment results in a 10% loss (see Table 2-1). The 18% difference is called roll return and is the result of the downward-sloping futures curve, which we have assumed in this example. In addition, the futures investment earns interest on the collateral which, added to the excess return, represents the total return from a commodity futures investment.

We are by no means restricted to the nearby contract; we could have invested in the second nearby contract and rolled into the third nearby, and so on. Thus, we have a number of investment options along the commodity term structure that we call Rolling Maturity Futures (RMF). While the example above rolls the contract on a single day, in practice it is customary to mitigate some of the price risk (associated to rolling) by switching from one contract to another over a period of a few days (see the *RMF Indices* section below).

In the above example, a decrease in the spot price of the commodity resulted in a positive overall return on investment because of the roll effect. However, there is no guarantee that the roll return is going to be positive; in recent years, some of the commodities that have been predominantly in backwardation have turned into contango, having just generated significant negative roll return.

From a commodity futures investor perspective, the relevant benchmark is the total return. For risk modeling purposes, we are looking for a set of factors to "explain" the excess return above the risk-free rate. This naturally leads to the three versions of RMF returns.

2.2 RMF Indices

There are three components to the RMF total return: price return, roll return, and collateral return. The sum of price and roll return is referred to as *excess* return; the sum of excess return and collateral return is *total* return.

Total Return Index (RMFTR) measures a fully collateralized investment in the RMFs, taking into account the monthly rolling of contracts.

Excess Return Index (RMFER) measures the return earned from investing in the RMFs, taking into account the effect of monthly composition changes during the roll period.

Price Index (RMFPI): reflects the aggregate price levels of the contracts included in the RMFs.

Roll Return is the component of return that arises from rolling a long position through time, from one futures contract to another, in a sloping price curve environment. Roll return is defined by subtracting the percentage change in the Price Index from the Excess Return.

RMF excess returns capture the return on commodity futures investments. On non-roll days, return calculations are straightforward, since the portfolio consists of a single futures contract. The RMF return is then simply the percentage return of this contract.

We define roll days by following the same convention of the S&P GSCI commodity indices, thus rolling over a 5-day period between the 5^{th} to 9^{th} business days of each month. On roll days, the excess return is calculated by aggregating the percentage returns of the outgoing and incoming futures contracts by using the prior day's roll weights. For example, on the 6^{th} business day, the percentage return of the two contracts are aggregated using weights of 80% and 20% for the outgoing and incoming futures contract, respectively, to reflect the fact that the RMF is invested in that ratio at the end of the 5^{th} business day.

Appendix C provides more details about the calculation of the three RMF indices.

2.3 Construction

The set of Rolling Maturity Futures (RMF) for a given commodity provides the estimation universe used to construct the risk model. RMF's are designed to reflect the available market opportunities as measured by the open interest of different contracts along the futures curve. This is analogous to using the face amount outstanding to select the estimation universe in bond markets or market capitalization in equity markets. The choice of contracts defining the RMFs for a commodity in a given calendar month is guided by the historical distribution of open interest across the futures curve. More details about the RMF construction are provided in Appendix B.

The Rolling Maturity Futures (RMF) Template is a concise way of representing the constituents of the rolling maturity futures portfolios over time. See

Table A-2 in Appendix A for an example of a template for gold (GC).

The first column represents the observation month, while the remaining columns are the actual traded monthly futures contracts (denoted by their first delivery date) identifying the RMF for that observation month. So the number of columns minus one represents the number of rolling maturity futures, 10 in the example. A change in the RMF from the previous month signals that rolling from the previous month RMF (the outgoing contract) into a new RMF (the incoming contract) will take place in the given observation month. For example, for Gold in January 2009, the outgoing contract is February 1, 2009 while the incoming contract is April 1, 2009.

2.4 Average Maturity

The maturity of each Rolling Maturity Futures Portfolio changes daily within a band, from shortest just before the roll period to longest just after the roll period. We define the average RMF maturity of the Rolling Maturity Futures Portfolio as the average daily maturity during the estimation period. The concept of RMF average maturity will be used to derive factor exposures of futures contracts from exposures of the RMF contracts.

2.5 Coverage

COM1, the existing BIM commodity model, uses the total return S&P GSCI family of indices (MSCI Research, 2006). The overall index is comprised of 24 sub-indices that are grouped in five aggregate indices. The 24 sub-indices are derived from the futures prices of 24 distinct commodities that can be grouped in five commodity sectors.

COM2 extends the set of commodities to 34; see Table A-1 for the complete list. Compared to COM1, the new model adds two precious metals, two industrial metals, and six agricultural products.

For users of the 24 factors in COM1, the new model provides the corresponding COM2 first Rolling Maturity Futures as an effective substitute for risk purposes. Indeed, the correlation between each of the respective pairs of monthly returns series from January 2003 to December 2009 ranges from 99.5% for Brent Crude to 99.99% for Natural Gas.

3 Factors and Factor Exposures

3.1 Modeling Framework

We observe historical asset returns and we would like to find a minimal set of common market factors that explain the return variability. The unexplained portion of return is called specific return. Common factor and asset specific return distributions are then used for asset risk forecasts.

More formally, for *N* asset excess returns r_t, *N* asset specific returns u_t and *K* factors returns f_t

$$r_t = X_t f_t + u_t \qquad \text{Eq. (4.1)}$$

where X_t is the $N \times K$ matrix of exposures at time t. This equation states that the asset excess return for the period starting at time *t* is equal to the product for exposures and common factor returns plus the residual asset specific return. The common factor returns do not depend on the asset. Given factor exposures and asset returns on each given date, we regress f_t by minimizing the size of the residual u_t.

The estimation universe used in the regression is the set of RMFs associated with a particular commodity. Exposures of RMF assets to factors are obtained through Principal Component Analysis.

3.2 Principal Component Analysis

Commodity term structures exhibit a high level of correlation, that is, futures contracts along the curve are highly collinear. Variables are highly collinear when there are only a few important sources of information in the data that are common to many variables. Using Principal Component Analysis (PCA), we identify the number of factors (principal components) that explain a large fraction (e.g., 95%) of the historical variation in the term structure.

PCA should be applied to stationary data. Commodity futures data can exhibit at least two non-stationary features.

3.2.1 Samuelson effect

This refers to fact that the volatility of a futures price increases with approaching maturity date. This effect is present for virtually all commodity futures data.

3.2.2 Seasonality

Due to supply and demand cycles, some commodities are more volatile in the winter and less so in the summer. One such commodity is natural gas, for which high and uncertain heating demand in the winter creates a potential for supply disruptions. Agricultural commodities are typically more volatile just before the harvest. This is reflected in the futures price data, whereas the volatility of the term structure differs by observation season. Precious metals are not seasonal, while oil and its derivatives display mild seasonality.

Rolling Maturity Futures, introduced in chapter 2, provide a solution to the Samuelson effect. RMF maturity does change daily, but the variation is within a pre-defined band. This is why we can assume that RMF volatility changes mostly due to change in market expectations.

When modeling risk we explicitly choose not to model seasonality. Nevertheless, seasonality is reflected in an averaged way in the computed exposures and in the factor returns.

The inputs to the PCA procedure are the raw (i.e., not normalized) RMF excess returns from a particular estimation period. The RMF returns were winsorized[2] in order to reduce the influence of outliers. After filling in missing and winsorized returns by using Expectation Maximization, the estimated (with equal weights) covariance matrix was used to define the Principal Components and the exposures. Normalization is chosen so that the exposure of the first RMF equals one. This allows us to interpret the volatility of each factor for a given commodity model as the contribution to volatility corresponding to the first RMF.

3.3 Number of Factors

Table 3-1 provides a summary of the percentage variance explained by the individually selected factors and using the overall 2007-09 estimation period. With the exception of lean hogs (LH), the shift factor explains more than 90% of the variance for all commodities, and more than 95% for thirty commodities (refer to table 5.2 for a list of names associated to the commodity code).

Table 3-1. COM2 2007-09 PCA Summary.

name	#factors	%var	%S	%T	%B		name	#factors	%var	%S	%T
CL	3	99.84%	97.2%	2.4%	0.3%		CT	2	99.03%	97.5%	1.5%
CO	2	99.78%	98.6%	1.2%			C	2	99.62%	98.9%	0.8%
RB	2	99.87%	98.9%	0.9%			S	2	99.06%	97.1%	1.9%
HO	2	99.81%	99.3%	0.5%			SM	2	98.84%	95.6%	3.2%
GO	2	99.86%	99.1%	0.8%			BO	2	99.83%	99.6%	0.2%
NG	3	99.08%	93.2%	5.2%	0.6%		W	2	98.92%	96.4%	2.6%
GC	2	99.99%	99.7%	0.3%			KW	2	98.62%	96.3%	2.3%
SI	2	99.98%	99.9%	0.1%			MW	2	95.70%	91.2%	4.5%
PA	1	99.83%	99.8%				CC	2	99.75%	99.3%	0.5%
PL	1	99.95%	99.9%				KC	2	99.91%	99.7%	0.2%
HG	2	99.96%	99.5%	0.5%			CF	2	99.62%	97.6%	2.1%
AL	2	99.61%	97.6%	2.0%			SB	2	99.59%	97.5%	2.1%
CU	2	99.89%	98.7%	1.2%			QW	2	98.58%	95.6%	3.0%
NI	2	99.89%	99.4%	0.5%			JO	2	99.14%	97.5%	1.6%
PB	2	99.94%	99.6%	0.3%			LH	2	93.83%	82.4%	11.4%
SN	2	99.91%	99.4%	0.6%			LC	2	96.83%	91.6%	5.2%
ZI	2	99.90%	99.5%	0.4%			FC	2	97.64%	95.5%	2.1%

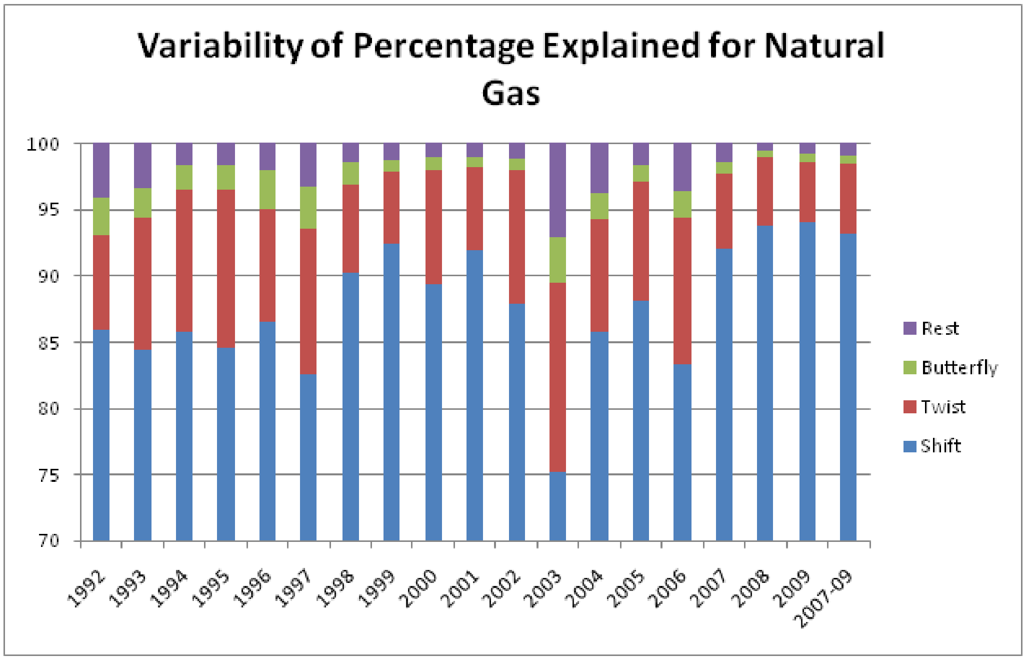
Some of the numbers for the twist and butterfly factors may look small. These percentages are computed using an estimation period in which the shift factor dominated compared to earlier periods.

Figure 3-1 shows the percentage of natural gas RMF excess returns explained by the three factors through time, assuming factors were updated yearly. It shows that, at least for some of the years, the

[2] We have chosen to exclude excess returns larger than ten standard deviations and replace excess returns that are between three and ten standard deviations with three standard deviations returns of the same sign.

use of three factors is justified, notably in 2003 when shift and twist factors explained less than 90% of variability.

Figure 3-1. Variability of Percentage Explained for Natural Gas.



3.4 Fixed Exposures

In general, the risk modeling framework allows for factor exposures to be time dependent. There is little reason to believe that this is the case for commodities in the chosen PCA approach. Figure 3.2 shows the crude oil (CL) shift factor exposures through time computed using a year of returns from 1998 until 2009, and in addition using one three-year period, 2007 through 2009, while Figure 3.3 plots the crude oil (CL) twist and butterfly factor exposures. The shapes, labeled “2007-09” and estimated using the most recent three years of data, have been used as representative shapes since the historical shapes do not deviate significantly across time.

To further investigate the validity of the fixed shape approach, we computed the percentage of variance of the RMF curve that would be explained by using the “2007-2009” fixed shapes in other calendar years. We found that the difference in variance explained (when compared to the numbers quoted in Figure 3-1) is always less than 1%, thus confirming our approach.

The number of the RMFs in existence changes with time, while the number of exposures is determined by the number of RMFs in existence during the estimation period. The number of RMFs in existence in the past is generally smaller, so a subset of the fixed exposures is used in the factor estimation. Similarly, in the future, the number of RMFs may increase and a method is needed to calculate the new exposures. See Appendix D for details of the methodology.

Figure 3-2. Crude Oil Shift Factor Exposures.

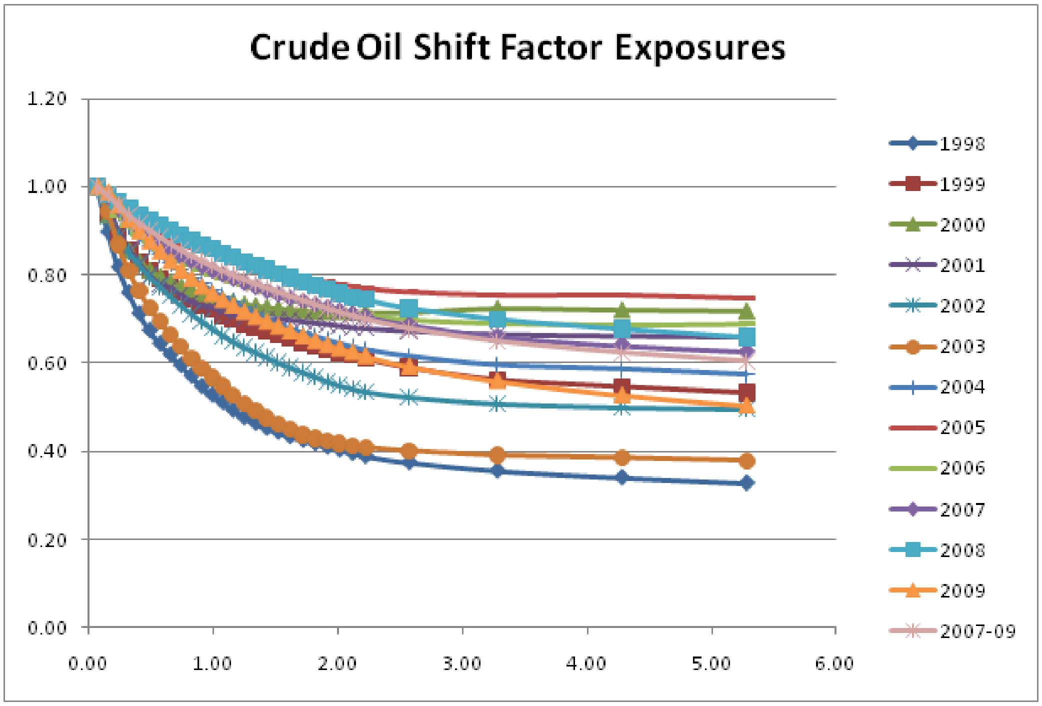
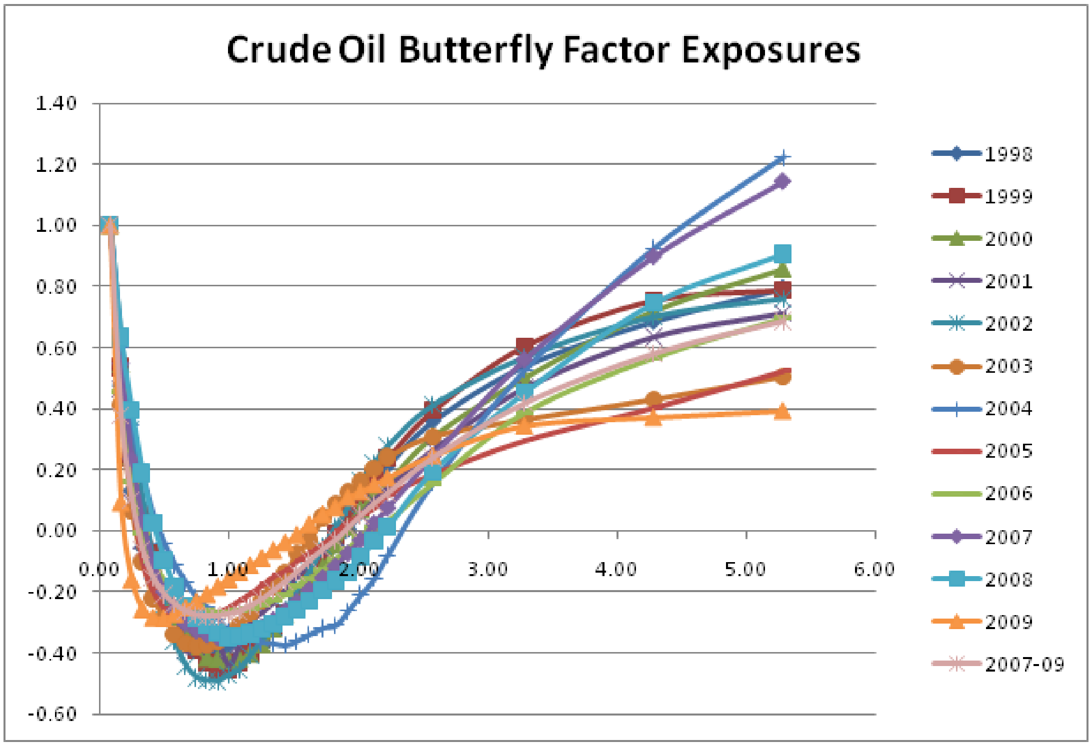
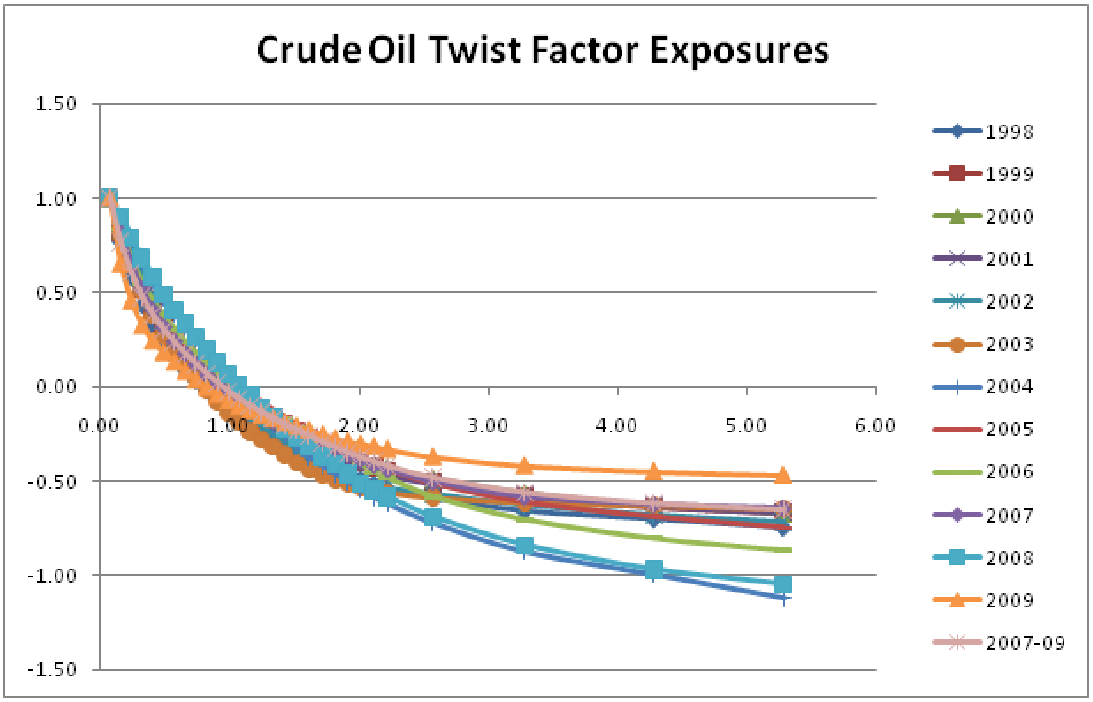


Figure 3-3. Crude Oil Twist and Butterfly Factor Exposures.





4 Factor Returns

4.1 Cross-sectional Regression

COM2 factor returns are estimated by daily multivariate regressions. The regressions minimize the sum of the squared residual returns and can be thought of as projections from the *N*-dimensional space of RMF excess returns to the *K*-dimensional space of factor returns.

RMF excess returns are equally-weighted in the COM2 regression. Using weights proportional to the square root of market capitalization is a standard convention in equity factor models. The product of open interest and previous market close could be considered a natural equivalent for individual commodity futures. However, since open interest tends to be highly concentrated in few of the first RMFs, we decided to use equal weighting to avoid substantially reducing the effective number of assets, and focusing almost exclusively on the short end of the curve.

4.2 Explanatory Power

An important summary statistic used to measure the explanatory power of regressions is the coefficient of determination, R^2, defined by

$$R^2 = 1 - \frac{\sum_n u_n^2}{\sum_n r_n^2}$$

where the summation is across all RMFs (see Eq. (4.1)).

Table 4-1 summarizes the explanatory power of cross-sectional regressions in COM2. The second column corresponds to the number of daily regressions performed, 99% of which have higher R^2 than the number in the third column. The fourth column is the median R^2, while the fifth is the median R^2using only the shift factor. The remaining columns give the contribution of each successive factor to the median R^2 (refer to table 5.2 for a list of names associated to the commodity code).

Table 4-1. COM2 R-squared.

Name	Number of days	1st percentile	Median	Shift	Twist	Butterfly
CL	3671	74.78%	99.62%	93.38%	5.63%	0.61%
CO	3982	27.67%	98.81%	94.42%	4.39%	
RB	3611	64.54%	99.73%	97.51%	2.22%	
HO	4508	53.69%	99.46%	97.01%	2.45%	
GO	4252	26.38%	98.59%	95.14%	3.45%	
NG	3423	34.43%	97.35%	82.60%	12.41%	2.34%
GC	4489	79.35%	99.94%	99.71%	0.23%	
SI	4278	75.81%	99.96%	99.80%	0.16%	
PA	4449	96.86%	100.00%	100.00%		
PL	4466	97.48%	100.00%	100.00%		
HG	4500	48.82%	99.66%	98.60%	1.06%	
AL	1899	24.15%	98.51%	94.63%	3.88%	

CU	1898	38.87%	99.54%	98.16%	1.37%	
NI	1898	46.70%	99.65%	98.67%	0.98%	
PB	1896	56.20%	99.79%	99.15%	0.64%	
SN	1883	44.91%	99.96%	99.88%	0.08%	
ZI	1898	49.54%	99.70%	99.06%	0.64%	
CT	3617	14.42%	95.92%	88.51%	7.41%	
C	4515	32.74%	98.93%	96.67%	2.26%	
S	4534	33.33%	99.00%	96.94%	2.06%	
SM	4532	17.22%	96.91%	91.82%	5.09%	
BO	4533	20.91%	98.84%	96.78%	2.06%	
W	4531	20.62%	97.91%	93.35%	4.57%	
KW	4529	23.11%	98.64%	94.91%	3.73%	
MW	3437	17.15%	95.00%	86.27%	8.73%	
CC	4496	33.95%	99.59%	98.99%	0.60%	
KC	4498	30.29%	99.40%	98.10%	1.30%	
CF	4537	32.26%	99.53%	98.02%	1.52%	
SB	4499	27.09%	98.84%	94.82%	4.02%	
QW	4530	20.22%	96.87%	90.27%	6.60%	
JO	4498	19.47%	97.79%	93.47%	4.32%	
LH	4534	8.60%	92.02%	78.51%	13.51%	
LC	4536	13.47%	95.90%	85.21%	10.69%	
FC	4538	9.26%	96.23%	91.40%	4.83%	

4.3 Factor Return Characteristics

The t-statistic is a standard tool to evaluate the statistical significance of a factor estimate. It is defined as $t = f/se(f)$, where $se(f)$ is the standard error of the factor estimate. Under certain assumptions, the t-statistic has a t-distribution with $\left(N - N_f\right)$ degrees of freedom, where N is the number of RMF excess returns and N_f is the number of factors. The critical value for a two-sided 5% test is often taken to be approximately 2, but for commodities with fewer RMFs this critical value could exceed 2 in a significant way. The percentage of significant factor estimates gives a measure of overall factor significance. The time average of the squared t-statistic also gives an indication of factor strength with the caveat that this statistic is sensitive to outliers. Table 4-2 and Table 4-3 provide a summary of these two measures for each COM2 factor, including the annualized volatility, return, and Sharpe ratio.

Table 4-2. Characteristics of COM2 energy and metals factors.

name	factor name	% with |t|>2	Average t2	Volatility	Return	Sharpe Ratio
CL	CRUDEOIL_SHIFT	98.34%	6680.4	31.42%	20.06%	0.64
CL	CRUDEOIL_TWIST	92.73%	295.6	14.19%	-1.87%	-0.13
CL	CRUDEOIL_BFLY	78.97%	29.2	5.36%	-3.12%	-0.58
CO	BRENT_SHIFT	95.08%	879.8	31.36%	19.78%	0.63
CO	BRENT_TWIST	75.89%	25.5	9.23%	-0.74%	-0.08
RB	GAS_SHIFT	95.10%	1652.1	33.89%	21.60%	0.64
RB	GAS_TWIST	77.26%	31.7	9.39%	-2.54%	-0.27
HO	HEATOIL_SHIFT	97.03%	2200.3	29.61%	13.90%	0.47
HO	HEATOIL_TWIST	83.03%	40.2	8.25%	-3.67%	-0.44
GO	GASOIL_SHIFT	92.50%	559.7	27.87%	12.66%	0.45
GO	GASOIL_TWIST	64.44%	13.3	7.67%	-1.70%	-0.22
NG	NATGAS_SHIFT	96.26%	922.1	44.55%	17.55%	0.39
NG	NATGAS_TWIST	88.69%	85.0	17.71%	-15.04%	-0.85
NG	NATGAS_BFLY	72.92%	14.9	13.45%	-12.34%	-0.92
GC	GOLD_SHIFT	98.75%	17539.5	15.93%	3.76%	0.24
GC	GOLD_TWIST	86.57%	34.4	1.55%	0.56%	0.36
SI	SILVER_SHIFT	98.34%	18488.8	28.19%	9.51%	0.34
SI	SILVER_TWIST	75.50%	18.2	2.56%	0.06%	0.02
PA	PALLADIUM	93.50%	156205.9	32.45%	14.41%	0.44
PL	PLATINUM	90.63%	805147.8	21.88%	12.02%	0.55
HG	NYCOPPER_SHIFT	94.80%	2888.5	26.05%	13.16%	0.51
HG	NYCOPPER_TWIST	68.16%	15.4	4.60%	0.30%	0.07
AL	ALUMINUM_SHIFT	96.95%	1922.7	22.54%	10.31%	0.46
AL	ALUMINUM_TWIST	86.78%	47.3	7.32%	-2.96%	-0.40
CU	COPPER_SHIFT	97.42%	6726.0	32.23%	31.39%	0.97
CU	COPPER_TWIST	87.41%	58.3	8.38%	-1.03%	-0.12
NI	NICKEL_SHIFT	97.73%	3752.7	41.97%	29.36%	0.70
NI	NICKEL_TWIST	81.03%	23.9	10.88%	-3.26%	-0.30
PB	LEAD_SHIFT	97.36%	4406.3	38.53%	34.80%	0.90
PB	LEAD_TWIST	82.07%	29.7	8.40%	-1.63%	-0.19
SN	TIN_SHIFT	97.19%	65571.3	32.00%	25.38%	0.79
SN	TIN_TWIST	77.75%	25.8	4.42%	0.13%	0.03
ZI	ZINC_SHIFT	97.73%	4096.6	35.08%	23.03%	0.66
ZI	ZINC_TWIST	75.82%	18.9	5.99%	-4.62%	-0.77

Table 4-3. Characteristics of COM2 agriculture and livestock factors.

name	factor name	% with |t|>2	Average t2	Volatility	Return	Sharpe Ratio
CT	COTTON_SHIFT	87.25%	116.6	23.44%	-7.01%	-0.30
CT	COTTON_TWIST	46.09%	5.2	6.48%	-4.45%	-0.69
C	CORN_SHIFT	83.34%	248.6	23.73%	-3.30%	-0.14
C	CORN_TWIST	22.17%	3.8	4.53%	-3.41%	-0.75
S	SOYBEANS_SHIFT	84.05%	209.7	22.11%	5.47%	0.25
S	SOYBEANS_TWIST	24.42%	3.8	5.13%	1.03%	0.20
SM	SBMEAL_SHIFT	87.33%	146.4	23.29%	7.53%	0.32
SM	SBMEAL_TWIST	46.38%	5.7	7.50%	2.99%	0.40
BO	SBOIL_SHIFT	90.93%	365.5	22.35%	4.33%	0.19
BO	SBOIL_TWIST	40.22%	4.7	3.71%	-1.42%	-0.38
W	WHEAT_SHIFT	70.93%	106.7	25.46%	0.44%	0.02
W	WHEAT_TWIST	16.86%	3.0	6.20%	-4.54%	-0.73
KW	KSWHEAT_SHIFT	53.96%	105.1	23.43%	2.76%	0.12
KW	KSWHEAT_TWIST	13.18%	3.0	6.24%	-1.91%	-0.31
MW	MNWHEAT_SHIFT	73.06%	49.5	22.12%	-0.37%	-0.02
MW	MNWHEAT_TWIST	21.79%	2.6	8.48%	-0.26%	-0.03
CC	COCOA_SHIFT	94.17%	1201.5	29.41%	1.90%	0.06
CC	COCOA_TWIST	35.50%	4.0	2.99%	-0.75%	-0.25
KC	COFFEE_SHIFT	91.60%	957.2	35.71%	0.81%	0.02
KC	COFFEE_TWIST	49.64%	7.4	8.42%	0.82%	0.10
CF	RBCOFFEE_SHIFT	85.94%	614.8	32.68%	4.75%	0.15
CF	RBCOFFEE_TWIST	26.58%	5.5	5.50%	2.78%	0.51
SB	SUGAR_SHIFT	79.80%	188.7	29.84%	9.92%	0.33
SB	SUGAR_TWIST	23.76%	5.0	5.86%	-0.86%	-0.15
QW	WHSUGAR_SHIFT	79.98%	108.3	21.17%	11.25%	0.53
QW	WHSUGAR_TWIST	35.32%	4.7	7.32%	2.52%	0.34
JO	OJ_SHIFT	87.82%	212.2	28.72%	-6.75%	-0.24
JO	OJ_TWIST	42.31%	5.4	6.31%	-0.51%	-0.08
LH	HOGS_SHIFT	70.00%	30.6	20.75%	2.55%	0.12
LH	HOGS_TWIST	28.67%	3.3	9.35%	-7.47%	-0.80
LC	CATTLE_SHIFT	67.53%	49.2	12.26%	1.95%	0.16
LC	CATTLE_TWIST	21.78%	3.6	4.41%	-1.69%	-0.38
FC	FDRCATTLE_SHIFT	78.16%	73.1	13.04%	3.09%	0.24
FC	FDRCATTLE_TWIST	18.11%	2.0	2.19%	-1.09%	-0.50

5 Common Factor Risk and Specific Risk

5.1 Covariance Matrices

In this paper we consider three variants of the model. Two of them, COM2S and COM2L, are component models used in the Barra Integrated Model (BIM). As such, they derive their factor covariance matrices from weekly factor returns, obtained by compounding daily returns. The third variant is a standalone model, which uses a monthly factor covariance matrix derived from daily data.

In all cases, the covariance matrices are calculated using exponential weighting so that more weight is placed on recent factor returns, thus reducing the influence of past returns on forecast. Daily EWMA covariance matrices are calculated as follows:

$$C_{kl}^{(d)} = cov(f_k, f_l)_{\ t} = \sum_{s=t-h}^{t} \lambda^{t-s} \, (f_{k,s} - \bar{f_k})(f_{l,s} - \bar{f_l}) \Big/ \sum_{s=t-h}^{t} \lambda^{t-s}$$

$$\bar{f_k} = \sum_{s=t-h}^{t} \lambda^{t-s} \, f_{k,s} \Big/ \sum_{s=t-h}^{t} \lambda^{t-s}$$

Here, h is the sample size while λ is related to the half-life parameter of the model (τ), defined as $\lambda = 0.5^{1/\tau}$. In other words, if the return at time *t* has a weight of 1, then τ sample returns in the past, the return weight becomes one half. Note that the formula applies the same half-life to all covariance terms, while in practice different half-lives are used for the volatility and correlation estimates.

Table 5-1 lists the half-lives of the COM2 variants. The “S” variant has a shorter half-life than the “L” variant and produces more accurate monthly forecasts, while the latter is less sensitive to market changes and creates more stable forecasts.

In order to scale up daily and weekly forecasts to a monthly horizon, the Newey-West serial correction procedure is applied(Newey & West, 1987). This correction combines the daily (or weekly) contemporaneous covariance matrix and the lagged daily (or weekly) covariance matrix. The Newey-West parameter in Table 5-1 specifies the number of lags used (in days or weeks).

Table 5-1. Covariance matrix parameters for COM2 variants.

Model Variant	Forecast Horizon	Return Frequency	Variance Half-life	Correlation Half-life	Newey-West	Sample Size
COM2S	monthly	weekly	18	104	2	NA
COM2L	monthly	weekly	52	156	2	NA
COM2	monthly	daily	90	90	10	540

Missing factor returns are preprocessed using an Expectation Maximization algorithm. The augmented returns history is then used to calculate the factor covariance matrix.

See section 7.2 for details on risk forecasting performance.

5.2 Specific Risk

Specific risk is the part of asset return volatility that cannot be explained by common factors. Factor models like COM2 assume that specific risk is fully diversifiable, meaning that the correlation between specific returns of different assets is zero.

COM2 uses two distinct approaches for estimating the specific risk of RMF and futures contracts. First, a time series methodology is used to estimate RMF specific risk from the long time series of RMF specific returns. Second, specific risk of any futures contract is estimated via interpolation of RMF specific risk forecasts along the maturity dimension.

Daily RMF specific risk forecasts are calculated using exponentially weighted averaging of daily specific returns:

$$\sigma_{u,d}^2 = \sum_{s=t-h}^{t} \lambda^{t-s} (u_s - \bar{u}) \Bigg/ \sum_{s=t-h}^{t} \lambda^{t-s}, \qquad \lambda = 0.5^{1/\tau}$$

$$\bar{u} = \sum_{s=t-h}^{t} \lambda^{t-s} u_s / \sum_{s=t-h}^{t} \lambda^{t-s}$$

As before, the half-life τ determines how quickly a past observation loses influence on the current forecast.

For monthly forecasts, COM2 calculates daily forecasts with a half-life of 90 days and a maximum of 540 daily specific returns. To scale up these daily forecasts, the Newey-West serial correction procedure with 10 lags is applied.

To calculate futures specific risk forecast, COM2 linearly interpolates RMF specific risk. Suppose that there are *N* RMFs with average maturities T_i and RMF specific risk forecasts $\sigma_u(T_i)$. The specific risk forecast of a futures contract with maturity T, $\sigma_e(T)$ is given by

$$\sigma_e(T) = \begin{cases} \sigma_u(T_1), \quad T < T_1, \\ \frac{T_{i+1}-T}{T_{i+1}-T_i}\sigma_u(T_i) + \frac{T-T_i}{T_{i+1}-T_i}\sigma_u(T_{i+1}), \; T_i \le T \le T_{i+1}, \; i = 1, \ldots, N-1 \\ \sigma_u(T_N), \quad T > T_N. \end{cases}$$

Due to the availability of long time series of RMF specific returns, the model has the capability of producing futures contracts specific risk forecasts as soon as they start trading.

See section 7.4 for details on risk forecasting performance.

6 Barra Integrated Model (BIM) Integration

6.1 Methodology

The way commodities are integrated in BIM has not changed substantially (MSCI Research, 2006). To summarize, integration proceeds in two steps:

1) **Build the local covariance matrix**. The monthly covariance is calculated from weekly local factor returns as described in Section 5.1.

2) **Integrate the local covariance matrix into the BIM covariance matrix.** Commodities are treated as a separate asset class, like bonds, equities, and currencies. A smaller set of "global" factors is used to link local factors across different asset classes ("global" and "core" factors are the same for commodities).

The BIM structural model links a local factor return f to a global factor return g as follows:

$$f = \beta g + \varphi,$$

where β is the local-global exposure, while φ is the purely local return. The exposure is a historical beta calculated with an exponentially-weighted time-series regression. A local commodity factor has exposure only to its corresponding global factor. For example, the SUGAR_TWIST factor is exposed only to the global agriculture factor.

6.2 COM2 Global Factors

It is a common practice to aggregate investable commodities into five groups: energy, precious metals, industrial metals, agriculture and livestock. COM1 uses the corresponding S&P GSCI aggregates as global factors, while COM2 calculates its own global factors. Nevertheless, the new global factors are highly correlated with the old.

COM2 global factors are portfolios of shift factors. For example, the global energy factor is a portfolio of the six energy shift factors. The yearly weights are determined using the following notion of capitalization.

Given a commodity curve with daily closing prices and open interests, we compute for each historical month the average realized price and the average realized open interest. These averages are computed by trimming the top and bottom 10% of the values in order to reduce the influence of outliers. We then define the average realized capitalization by the product of average realized price and average realized open interest. The sum of the average realized capitalization across all contracts gives the commodity average realized capitalization. Finally, we calculate the trailing 24 months moving average realized capitalization at the end of each October. The final weights for the following year are obtained by normalizing across all commodities in the sector.

In the case of industrial metals, where open interest data is not available, COM2 uses annual production data (U.S. Geological Survey). This data has a two-year lag so that, for example, when the 2010 weights are generated in October 2009, the production data used corresponds to 2007. In order to calculate capitalization, COM2 calculates the product of the average RMFPI for the year ending in October 2009 and the production data for 2007. Also, in the industrial metals global factor, we set the weight of HG (copper traded on NYMEX) to zero, using LME copper instead.

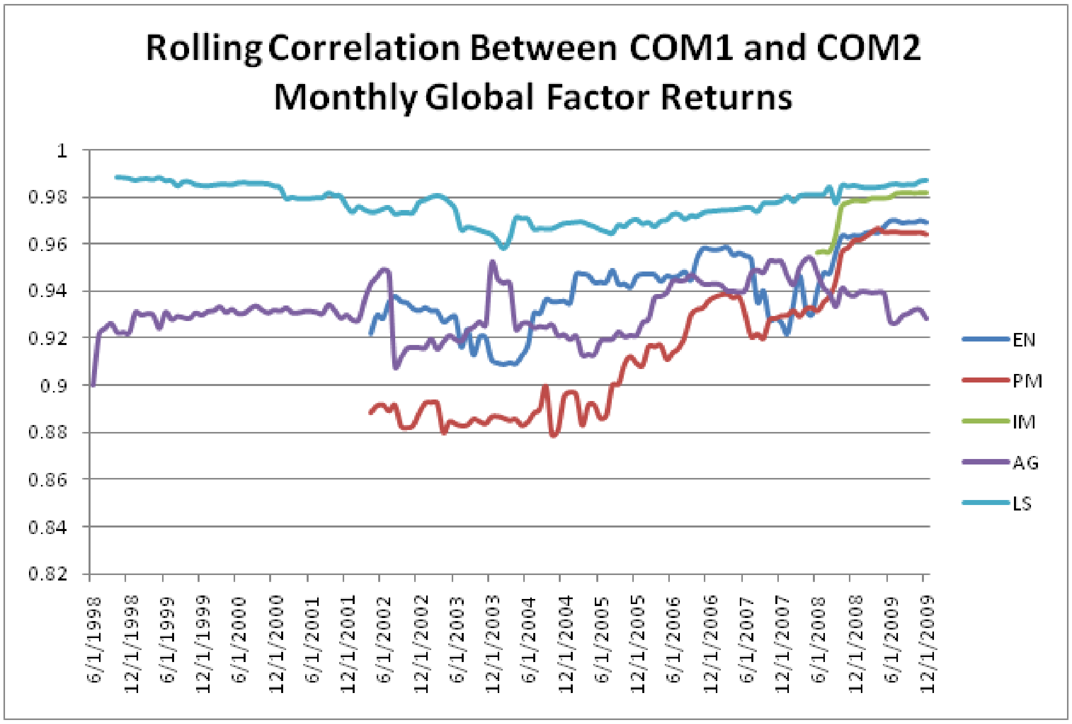
Table 6-1 gives the yearly commodity weights for 2010 for each of the five sectors. Oil dominates the energy sector with more than 50% of the weight. The precious metals sector is mostly gold, while aluminum and copper represent 70% of the industrial metals sector. Corn and soy are the two major agricultural commodities, while the livestock commodity sector is dominated by live cattle.

Table 6-1. COM2 commodity weights for 2010 within each of the five sectors.

Energy			**Agriculture**	
CL	37.22%		CT	0.61%
CO	18.06%		C	26.80%
RB	6.44%		S	25.61%
HO	8.04%		SM	0.06%
GO	10.01%		BO	7.16%
NG	20.23%		W	12.65%
			KW	3.92%
Precious Metals			MW	1.51%
GC	77.82%		CC	0.04%
SI	18.50%		KC	6.79%
PA	1.07%		CF	0.02%
PL	2.61%		SB	14.38%
			QW	0.02%
Industrial Metals			JO	0.44%
HG	0.00%			
AL	31.26%		**Livestock**	
CU	42.15%		LH	31.59%
NI	9.26%		LC	59.14%
PB	6.40%		FC	9.27%
SN	2.28%			
ZI	8.65%			

The new COM2 global factors and the COM1 global factors have similar risk characteristics. Figure 6-1 shows that correlation between monthly returns of corresponding pairs is above 90% most of the time.

Figure 6-1. Rolling Correlation between COM1 and COM2 Global Factor Returns (Energy, Precious Metals, Industrial Metals, Agriculture, Livestock).



7 Forecasting Performance

In this section we test the COM2 risk forecasting properties by examining the properties of a 12-month rolling bias statistics measure for each of the factors and for sets of commodity portfolios that, in our opinion, are representatives of typical commodity investment strategies. Testing the risk performance of individual RMF contracts covers investments in the S&P GSCI indices and other commodity indices, while testing portfolios of spreads along the RMF curve covers long-short positions along each commodity curve. Notice that in COM1 the risk forecast of single spread positions would be identically equal to zero; this is due to the fact that exposures of each contract to the single source of risk associated with any commodity is assumed to be constant along the entire futures curve.

7.1 Bias Tests

Bias statistics are a useful tool to test the forecasting performance of a risk model. These tests are applicable for any pair of time series of returns and accompanying risk forecasts, for single assets and well-diversified portfolios, and for any frequency (e.g., daily or monthly).

First, *out-of-sample* z-scores, $z_{t,q}$, are calculated:

$$z_{t,q} = \frac{r_{t+q}}{\sigma_t}$$

First, σ_t is the risk forecast at time t and r_{t+q} is the realized return of the entity at time $t+q$, where q is the forecast horizon. If the forecasts are perfect, the standard deviation of the z-scores is one. Over-forecasting results in standard deviation below one, while under-forecasting leads to a value larger than one.

Second, the bias statistic $b_{t,T}$, is defined as the sample standard deviation of the z-scores over a past time period T, where $\bar{z}_q$ denotes the mean z-score for each window:

$$b_{t,T} = \left(\frac{1}{T-1}\sum_{s=t-T+1}^{t}(z_{s,q} - \bar{z}_q)^2\right)^{1/2}$$

The bias statistic will deviate from one due to the finite sample used. If we assume that the returns are normally distributed, a 95% confidence interval for the bias statistic is given by

$$C_t = \left[1 - \sqrt{2/T}, 1 + \sqrt{2/T}\right]$$

When forecasting risk of undiversified portfolios, especially at higher frequencies, extreme returns happen with higher frequency than implied by the normal distribution. One simple measure of this effect is the return kurtosis, defined as the fourth central moment divided by the fourth power of the return standard deviation. The normal distribution has a kurtosis of 3.

A more general 95% confidence interval for the bias statistics (Connor, 2000) is given by

$$C_t = \left[1 - \sqrt{(k-1)/T}, 1 + \sqrt{(k-1)/T}\right]$$

where $k$is the estimated return kurtosis of all N returns:

$$k = \frac{\frac{1}{N}\sum_t (r_t - \bar{r})^4}{\left(\frac{1}{N}\sum_t (r_t - \bar{r})^2\right)^2}$$

All bias test results for monthly forecasts use a time period T equal to twelve months. Rolling bias statistics are then calculated and the percentage of all bias statistics within the expected confidence interval (C_t) is denoted by Q_P. This gives a measure of the forecasting performance for portfolio P:

$$Q_P = n(b_{P,t,T} \in C_t)/n(b_{P,t,T}).$$

7.1.1 Robust Bias Tests

The bias statistic is highly sensitive to outliers. To control for the influence of outliers, we also calculate a robust bias statistic (MSCI Research, 2010) by using winsorized z-scores:

$$\tilde{z}_{t,q} = \max(-3, \min(+3, z_{t,q})).$$

7.1.2 RAD Statistic

The Rolling Absolute Deviation (RAD) is another statistical measure used to summarize a time series of bias statistics. It is calculated by first obtaining the absolute deviation, $AD_{t,T}$, of a single bias statistic from one:

$$AD_{t,T} = |b_{t,T} - 1|.$$

The RAD statistic is then the time series average of the absolute deviations over the period $[t_0, t_1]$:

$$RAD_{t_0,t_1,T} = \frac{1}{t_1 - t_0} \sum_{t=t_0}^{t_1} AD_{t,T}.$$

7.2 Forecasting Factor Risk

The following two tables present the Q-statistic from the rolling 12-month bias test on monthly factor returns and forecasts. As described in Section 5.1, these forecasts are obtained using a EWMA estimator with an autocorrelation correction. The average Q-statistic is 87%, with a minimum of 67% for a soybeans twist factor.

Table 7-1. Robust and raw (in brackets) rolling 12-month bias test for COM2 energy and metals factors. The table lists the number of monthly returns and the percentage of observations that fall within the confidence interval of the test.

name	factor name	# of returns	Q statistic
CL	CRUDEOIL_SHIFT	163	86.2% (86.2%)
CL	CRUDEOIL_TWIST	163	92.8% (92.1%)
CL	CRUDEOIL_BFLY	163	80.3% (77.6%)
CO	BRENT_SHIFT	175	90.2% (90.2%)
CO	BRENT_TWIST	175	92.1% (89.6%)
RB	GAS_SHIFT	160	85.2% (79.9%)
RB	GAS_TWIST	160	85.9% (78.5%)
HO	HEATOIL_SHIFT	203	89.6% (88.0%)
HO	HEATOIL_TWIST	203	93.2% (91.1%)
GO	GASOIL_SHIFT	188	90.4% (88.7%)
GO	GASOIL_TWIST	188	83.6% (78.5%)
NG	NATGAS_SHIFT	151	86.4% (74.3%)
NG	NATGAS_TWIST	151	90.7% (90.7%)

NG	NATGAS_BFLY	151	79.3% (77.9%)
GC	GOLD_SHIFT	203	84.4% (77.6%)
GC	GOLD_TWIST	203	88.5% (82.3%)
SI	SILVER_SHIFT	193	83.5% (83.5%)
SI	SILVER_TWIST	193	85.7% (68.7%)
PA	PALLADIUM	203	92.2% (77.6%)
PL	PLATINUM	203	81.3% (78.1%)
HG	NYCOPPER_SHIFT	203	76.0% (56.8%)
HG	NYCOPPER_TWIST	203	93.2% (82.3%)
AL	ALUMINUM_SHIFT	77	84.8% (81.8%)
AL	ALUMINUM_TWIST	77	100.0% (100.0%)
CU	COPPER_SHIFT	77	84.8% (57.6%)
CU	COPPER_TWIST	77	90.9% (89.4%)
NI	NICKEL_SHIFT	77	92.4% (92.4%)
NI	NICKEL_TWIST	77	89.4% (89.4%)
PB	LEAD_SHIFT	77	95.5% (75.8%)
PB	LEAD_TWIST	77	95.5% (89.4%)
SN	TIN_SHIFT	77	98.5% (80.3%)
SN	TIN_TWIST	77	68.2% (60.6%)
ZI	ZINC_SHIFT	77	95.5% (81.8%)
ZI	ZINC_TWIST	77	69.7% (62.1%)

Table 7-2. Robust and raw (in brackets) rolling 12-month bias test for COM2 agricultural and livestock factors. The table lists the number of monthly returns and the percentage of observations that fall within the confidence interval of the test.

name	factor name	# of returns	Q statistic
CT	COTTON_SHIFT	161	80.7% (80.0%)
CT	COTTON_TWIST	161	90.0% (82.7%)
C	CORN_SHIFT	203	93.8% (92.2%)
C	CORN_TWIST	203	84.9% (76.0%)
S	SOYBEANS_SHIFT	203	82.3% (82.3%)
S	SOYBEANS_TWIST	203	66.7% (52.1%)
SM	SBMEAL_SHIFT	203	90.1% (87.5%)
SM	SBMEAL_TWIST	203	88.5% (80.7%)
BO	SBOIL_SHIFT	203	82.3% (72.9%)
BO	SBOIL_TWIST	203	77.1% (77.1%)
W	WHEAT_SHIFT	203	100.0% (100.0%)
W	WHEAT_TWIST	203	84.4% (74.5%)
KW	KSWHEAT_SHIFT	203	94.8% (82.8%)
KW	KSWHEAT_TWIST	203	84.4% (81.3%)
MW	MNWHEAT_SHIFT	151	82.1% (77.9%)

MW	MNWHEAT_TWIST	151	82.1% (77.9%)
CC	COCOA_SHIFT	203	74.0% (67.7%)
CC	COCOA_TWIST	203	91.1% (82.8%)
KC	COFFEE_SHIFT	203	76.6% (70.3%)
KC	COFFEE_TWIST	203	84.9% (82.3%)
CF	RBCOFFEE_SHIFT	203	81.8% (70.8%)
CF	RBCOFFEE_TWIST	203	88.5% (74.5%)
SB	SUGAR_SHIFT	203	86.5% (83.3%)
SB	SUGAR_TWIST	203	89.1% (78.1%)
QW	WHSUGAR_SHIFT	203	85.9% (73.4%)
QW	WHSUGAR_TWIST	203	89.6% (80.2%)
JO	OJ_SHIFT	203	95.3% (95.3%)
JO	OJ_TWIST	203	93.8% (84.9%)
LH	HOGS_SHIFT	203	93.8% (93.2%)
LH	HOGS_TWIST	203	91.1% (84.9%)
LC	CATTLE_SHIFT	203	81.8% (70.3%)
LC	CATTLE_TWIST	203	87.0% (83.3%)
FC	FDRCATTLE_SHIFT	203	95.3% (91.1%)
FC	FDRCATTLE_TWIST	203	84.9% (79.2%)

7.3 Forecasting RMF Risk

The forecasting performance of COM2 is evaluated on typical portfolios held by commodity investors.

Many long-only portfolios held by commodity investors track the S&P GSCI. We begin by testing the COM2 monthly forecasting performance of similar portfolios consisting of the first RMF in each commodity class over the whole history available.

Table 7-3 lists the number of monthly returns, together with the robust and raw (in brackets) rolling 12-month bias tests. The numbers for the robust tests are on average 6% larger than the raw test, indicating a relatively large number of extreme returns in these undiversified portfolios.

Table 7-3. Robust and raw (in brackets) rolling 12-month bias test. The table lists the number of monthly returns and the percentage of observations that fall within the confidence interval of the test.

Name	# of Returns	Bias stat		Name	# of Returns	Bias stat
CL	163	90.8% (89.5%)		CT	161	82.7% (82.0%)
CO	175	87.8% (86.0%)		C	203	93.8% (93.2%)
RB	160	82.6% (73.8%)		S	203	81.3% (80.2%)
HO	203	90.6% (88.5%)		SM	203	89.6% (87.5%)
GO	188	85.3% (78.0%)		BO	203	85.9% (75.5%)
NG	151	90.7% (83.6%)		W	203	100.0% (95.3%)
GC	203	85.4% (77.6%)		KW	203	91.1% (77.1%)

SI	193	86.8% (85.2%)		MW	151	81.4% (77.9%)
PA	203	92.2% (77.6%)		CC	203	75.0% (68.8%)
PL	203	81.3% (78.1%)		KC	203	75.0% (68.8%)
HG	203	75.0% (60.4%)		CF	203	83.3% (72.9%)
AL	77	84.8% (84.8%)		SB	203	85.4% (83.9%)
CU	77	93.9% (56.1%)		QW	203	92.7% (85.9%)
NI	77	92.4% (92.4%)		JO	203	99.0% (99.0%)
PB	77	90.9% (83.3%)		LH	203	91.7% (89.6%)
SN	77	98.5% (81.8%)		LC	203	83.3% (78.6%)
ZI	77	90.9% (90.9%)		FC	203	92.2% (87.0%)

For many commodities, the assumption of normality for monthly RMF returns is inadequate. To account for the increased likelihood of abnormal returns, we perform the rolling 12-month bias test using the wider confidence intervals obtained with the kurtosis correction. Table 7-4 lists the sample kurtosis of monthly returns and the percentage of bias statistics falling inside the confidence interval. This number increases by more than 7% on average with the largest increases strongly associated with higher sample kurtosis.

Table 7-4. Robust and raw (in brackets) rolling 12-month bias test with kurtosis correction. The table lists sample kurtosis of the monthly returns and the percentage of observations that fall within the confidence interval of the test.

Name	Kurtosis	Bias stat		Name	Kurtosis	Bias stat
CL	3.59	92.8% (92.1%)		CT	3.74	96.0% (91.3%)
CO	4.25	96.3% (91.5%)		C	3.53	97.4% (96.4%)
RB	4.30	94.6% (79.2%)		S	3.88	87.0% (85.9%)
HO	4.07	93.2% (92.2%)		SM	3.94	94.8% (90.6%)
GO	3.73	90.4% (89.3%)		BO	4.84	90.6% (82.3%)
NG	3.59	92.1% (88.6%)		W	3.20	100.0% (96.4%)
GC	4.90	100.0% (88.0%)		KW	3.94	95.3% (84.9%)
SI	3.62	91.2% (85.7%)		MW	6.30	90.7% (87.1%)
PA	6.42	100.0% (81.8%)		CC	4.32	89.1% (79.7%)
PL	7.79	97.4% (89.1%)		KC	5.45	98.4% (92.2%)
HG	5.88	98.4% (87.0%)		CF	6.84	99.0% (85.4%)
AL	3.41	89.4% (89.4%)		SB	3.45	90.6% (90.1%)
CU	5.42	100.0% (78.8%)		QW	3.05	92.7% (85.9%)
NI	2.90	92.4% (92.4%)		JO	3.79	100.0% (100.0%)
PB	3.24	92.4% (90.9%)		LH	3.60	93.2% (92.7%)
SN	3.55	100.0% (86.4%)		LC	6.11	100.0% (94.8%)
ZI	4.56	98.5% (98.5%)		FC	3.93	97.4% (91.7%)

Table 7-5 provides a summary of the robust and raw (in brackets) rolling 12-month bias tests for all RMFs and all commodities. The average Q-statistic is 86% with a minimum of 74% for cocoa.

Table 7-5. Summary of robust and raw (in brackets) rolling 12-month bias test for all commodities and all RMFs. The table lists the minimum, average and maximum percentage of observations that fall within the confidence interval of the test.

name	min	average	max
CL	76.3% (74.3%)	84.9% (83.7%)	90.8% (90.1%)
CO	78.9% (75.9%)	87.9% (87.2%)	90.9% (90.2%)
RB	82.6% (73.8%)	85.6% (81.1%)	87.9% (84.6%)
HO	77.7% (77.7%)	87.9% (86.3%)	91.1% (90.6%)
GO	75.7% (65.8%)	88.3% (83.8%)	92.1% (90.4%)
NG	72.1% (67.1%)	84.4% (76.6%)	93.6% (85.3%)
GC	83.4% (75.2%)	84.6% (77.8%)	85.4% (78.6%)
SI	81.9% (81.9%)	84.1% (83.5%)	86.8% (85.2%)
PA	76.3% (67.8%)	84.2% (72.7%)	92.2% (77.6%)
PL	73.0% (59.5%)	77.1% (68.8%)	81.3% (78.1%)
HG	74.5% (54.0%)	76.2% (58.2%)	78.6% (61.5%)
AL	84.8% (72.7%)	87.3% (81.0%)	89.4% (89.4%)
CU	75.8% (53.0%)	86.8% (57.1%)	93.9% (65.2%)
NI	92.4% (92.4%)	92.7% (92.4%)	95.5% (92.4%)
PB	90.9% (74.2%)	93.9% (76.5%)	95.5% (83.3%)
SN	93.9% (75.8%)	97.1% (79.3%)	98.5% (81.8%)
ZI	86.4% (72.7%)	90.3% (80.2%)	95.5% (90.9%)
CT	82.0% (78.0%)	83.0% (80.7%)	84.0% (83.3%)
C	92.2% (90.8%)	93.5% (92.5%)	95.3% (95.3%)
S	72.9% (70.8%)	80.2% (79.7%)	84.4% (84.4%)
SM	71.4% (71.4%)	87.9% (86.8%)	93.9% (93.9%)
BO	62.2% (59.5%)	79.9% (71.2%)	85.9% (76.0%)
W	98.4% (93.2%)	99.7% (97.2%)	100.0% (100.0%)
KW	91.1% (77.1%)	94.9% (86.9%)	98.4% (97.7%)
MW	79.1% (72.1%)	84.9% (79.0%)	94.4% (85.7%)
CC	72.9% (66.7%)	74.0% (67.7%)	75.0% (68.8%)
KC	75.0% (68.8%)	76.2% (71.1%)	79.2% (72.9%)
CF	79.2% (68.8%)	81.8% (70.2%)	83.3% (72.9%)
SB	84.4% (79.7%)	85.8% (82.7%)	87.5% (83.9%)
QW	74.7% (63.3%)	85.9% (73.1%)	92.7% (85.9%)
JO	94.3% (91.7%)	96.0% (95.4%)	99.0% (99.0%)
LH	83.3% (71.8%)	91.3% (87.9%)	96.9% (96.4%)
LC	76.6% (70.8%)	83.5% (79.2%)	89.6% (85.9%)
FC	90.6% (87.0%)	92.1% (88.6%)	93.8% (90.1%)

7.4 Forecasting Specific Risk

In this section we test the individual RMF monthly specific risk forecasts. As described in Section 5.2, these are EWMA estimates with a correction for autocorrelations. The average Q-statistic is 83% with a minimum of 61% for platinum.

Table 7-6. Summary of robust and raw (in brackets) rolling 12-month bias test for RMF specific risk forecasts. The table lists the minimum, average and maximum percentage of observations that fall within the confidence interval of the test.

name	min	average	max
CL	77.0% (73.7%)	87.3% (82.6%)	96.7% (95.4%)
CO	87.2% (78.2%)	94.5% (86.4%)	99.4% (95.1%)
RB	81.2% (71.8%)	89.3% (82.2%)	98.4% (98.4%)
HO	79.2% (65.6%)	88.6% (78.5%)	93.2% (91.9%)
GO	79.7% (72.9%)	87.9% (83.7%)	94.4% (90.4%)
NG	64.3% (42.1%)	81.2% (72.4%)	95.0% (90.7%)
GC	76.0% (73.4%)	88.2% (83.8%)	97.9% (90.6%)
SI	64.8% (53.3%)	75.8% (63.3%)	82.4% (77.5%)
PA	83.3% (69.6%)	84.0% (69.6%)	84.7% (69.6%)
PL	60.5% (67.6%)	61.3% (67.6%)	62.2% (67.6%)
HG	69.3% (64.1%)	79.3% (75.4%)	89.6% (87.6%)
AL	77.3% (77.3%)	94.8% (93.5%)	100.0% (100.0%)
CU	74.2% (69.7%)	88.7% (81.8%)	100.0% (90.9%)
NI	71.2% (71.2%)	89.9% (86.4%)	98.5% (98.5%)
PB	63.6% (57.6%)	81.9% (79.9%)	92.4% (92.4%)
SN	57.6% (48.5%)	69.7% (64.1%)	80.3% (80.3%)
ZI	45.5% (34.8%)	69.5% (63.1%)	87.9% (87.9%)
CT	72.0% (64.7%)	84.2% (78.6%)	93.3% (93.3%)
C	70.8% (60.4%)	83.6% (68.4%)	90.8% (77.1%)
S	50.0% (32.8%)	66.0% (54.8%)	85.9% (79.2%)
SM	79.2% (64.6%)	87.8% (81.1%)	100.0% (100.0%)
BO	64.1% (52.1%)	73.5% (65.3%)	86.5% (86.5%)
W	61.7% (59.6%)	76.7% (71.2%)	87.0% (81.8%)
KW	74.2% (71.9%)	78.9% (74.6%)	84.4% (79.1%)
MW	39.5% (34.9%)	76.4% (73.2%)	87.3% (84.1%)
CC	72.9% (72.9%)	84.5% (80.9%)	95.8% (90.1%)
KC	68.4% (66.1%)	78.6% (75.2%)	98.7% (98.7%)
CF	86.5% (66.1%)	91.8% (80.2%)	95.3% (93.8%)
SB	89.6% (87.5%)	92.8% (91.9%)	95.3% (94.8%)
QW	82.8% (81.8%)	90.3% (87.2%)	94.8% (91.1%)
JO	75.5% (62.5%)	83.2% (77.0%)	92.7% (92.7%)
LH	91.1% (88.0%)	94.5% (93.1%)	100.0% (100.0%)

LC	88.0% (80.7%)	93.5% (91.9%)	95.8% (95.8%)
FC	81.3% (80.2%)	85.5% (84.1%)	91.1% (90.6%)

7.5 Forecasting Spread Risk

In this section, we test the ability of COM2 to forecast spread risk. We focus on RMF spread risk and examine the performance of four spread portfolios that consist of a long first RMF position and a short position in longer maturity RMFs. The average maturity difference is closest to two, four, six, and twelve months, respectively. For these spread portfolios, Table 7-7 presents the Q-statistic from the rolling 12-month bias tests. Between the two RMF positions, performance improves for spreads corresponding to increasing differences in maturity. Energy, agricultural and livestock sectors perform reasonably well, while precious metals (excluding palladium and platinum) and industrial metals (excluding New York copper and tin) display underperformance, especially for the first spread. We find that underperformance in this case is due to over-forecasting of spread risk.

To judge COM2 performance, we used a EWMA estimator of spread risk and found that EWMA has a definite advantage (19.5% on average) for the first spread, which gradually diminishes as the spread increases, causing a small COM2 advantage for the last spread (1% on average). In addition, switching off specific risk was found to help underperformers and hurt good performers. See Appendix E for more details.

Our tentative conclusion is that the assumption of a diagonal covariance matrix of RMF specific returns has limitations, especially when forecasting spread risk of RMFs or futures contracts with close maturities. In this case, specific risk tends to dominate the forecast and we believe that failure to include a positive cross-correlation of specific returns in the spread risk forecast results in over-forecasting.

Table 7-7. This table shows a robust rolling 12-month bias test for four RMF spread portfolios, listing the percentage of observations that fall within the confidence interval of the test.

	RMF_1_2	RMF_1_4	RMF_1_6	RMF_1_12
CL	57.2%	79.6%	90.1%	94.7%
CO	90.2%	79.3%	81.7%	87.2%
RB	83.9%	85.9%	82.6%	81.9%
HO	80.2%	82.3%	91.7%	90.6%
GO	74.6%	75.1%	78.0%	84.2%
NG	55.0%	76.4%	82.1%	87.9%
GC	13.5%	13.5%	35.9%	51.0%
SI	28.6%	28.6%	47.3%	69.8%
PA	89.1%	89.1%	89.1%	89.1%
PL	72.9%	72.9%	72.9%	72.9%
HG	79.2%	79.2%	72.9%	81.3%
AL	0.0%	59.1%	77.3%	84.8%
CU	0.0%	36.4%	45.5%	56.1%
NI	3.0%	24.2%	34.8%	50.0%

PB	33.3%	80.3%	87.9%	90.9%
SN	69.7%	78.8%	74.2%	63.6%
ZI	1.5%	60.6%	66.7%	68.2%
CT	85.3%	85.3%	82.7%	85.3%
C	82.3%	82.3%	96.9%	93.2%
S	52.1%	52.1%	64.1%	84.4%
SM	75.5%	76.0%	82.3%	89.6%
BO	77.6%	56.3%	66.1%	91.7%
W	59.4%	59.4%	67.2%	89.1%
KW	53.1%	53.1%	78.1%	83.9%
MW	81.4%	81.4%	81.4%	82.1%
CC	70.3%	70.3%	82.3%	88.5%
KC	69.8%	69.8%	64.6%	82.3%
CF	74.5%	81.8%	83.9%	83.9%
SB	79.7%	79.7%	84.9%	86.5%
QW	82.8%	82.8%	85.4%	91.1%
JO	73.4%	73.4%	93.2%	98.4%
LH	87.5%	96.4%	91.7%	90.1%
LC	60.4%	60.4%	85.9%	84.4%
FC	65.1%	63.0%	80.2%	80.2%
Average	**60.7%**	**68.4%**	**75.9%**	**82.0%**

7.6 Forecasting Futures Risk

This section explores the daily forecasting performance on portfolios consisting of long positions in individual futures contracts. Table 7-8 lists the percentage of bias statistics inside a 95% confidence interval, together with the number of futures contracts used and the minimum, average and maximum bias statistic. The best performance is observed for crude oil (CL), while the worst for palladium (PA).

Table 7-8. Robust and raw (in brackets) daily bias stats for futures contracts computed over the last three months of trading.

name	% BS inside CI	# of contracts	min BS	mean BS	max BS
CL	92.4% (84.8%)	171	0.72 (0.72)	1.02 (1.04)	1.38 (1.55)
CO	89.0% (80.8%)	182	0.72 (0.72)	1.02 (1.04)	1.35 (1.48)
RB	91.1% (84.5%)	168	0.74 (0.74)	1.04 (1.06)	1.30 (1.56)
HO	85.8% (81.0%)	211	0.79 (0.79)	1.04 (1.06)	1.40 (1.59)
GO	88.2% (80.0%)	195	0.80 (0.80)	1.04 (1.07)	1.41 (1.56)
NG	77.4% (71.7%)	159	0.62 (0.62)	1.02 (1.04)	1.34 (1.94)
GC	80.9% (68.9%)	209	0.60 (0.60)	0.98 (1.04)	1.38 (1.77)
SI	88.4% (77.4%)	199	0.72 (0.72)	0.99 (1.04)	1.33 (1.54)
PA	68.1% (52.8%)	72	0.65 (0.71)	1.00 (1.07)	1.35 (1.75)

PL	87.3% (77.5%)	71	0.75 (0.75)	1.00 (1.06)	1.29 (2.51)
HG	83.9% (72.0%)	211	0.76 (0.76)	1.04 (1.09)	1.48 (1.82)
AL	83.5% (83.5%)	85	0.69 (0.69)	0.98 (1.02)	1.28 (1.39)
CU	85.9% (83.5%)	85	0.69 (0.77)	0.99 (1.01)	1.38 (1.42)
NI	81.2% (76.5%)	85	0.70 (0.70)	0.99 (1.01)	1.38 (1.39)
PB	89.4% (80.0%)	85	0.71 (0.71)	1.01 (1.04)	1.27 (1.39)
SN	78.8% (60.0%)	85	0.58 (0.58)	0.96 (1.04)	1.25 (1.36)
ZI	91.8% (85.9%)	85	0.79 (0.80)	1.00 (1.03)	1.22 (1.29)
CT	82.9% (72.9%)	70	0.75 (0.75)	1.05 (1.07)	1.39 (1.45)
C	80.4% (73.9%)	92	0.72 (0.72)	1.03 (1.06)	1.38 (1.43)
S	78.0% (69.9%)	123	0.67 (0.67)	1.01 (1.05)	1.35 (1.58)
SM	81.6% (73.0%)	141	0.69 (0.74)	1.01 (1.05)	1.32 (1.64)
BO	86.5% (83.0%)	141	0.71 (0.73)	1.01 (1.04)	1.39 (1.44)
W	88.6% (83.0%)	88	0.81 (0.81)	1.05 (1.09)	1.37 (3.04)
KW	84.1% (76.1%)	88	0.78 (0.78)	1.05 (1.08)	1.39 (1.62)
MW	87.9% (72.7%)	66	0.81 (0.81)	1.04 (1.09)	1.47 (2.16)
CC	90.9% (84.1%)	88	0.84 (0.84)	1.04 (1.08)	1.32 (1.42)
KC	87.5% (72.7%)	88	0.59 (0.59)	1.04 (1.10)	1.47 (1.97)
CF	69.5% (57.1%)	105	0.60 (0.60)	1.02 (1.11)	1.42 (2.81)
SB	91.8% (79.5%)	73	0.83 (0.84)	1.04 (1.12)	1.53 (3.41)
QW	84.1% (75.0%)	88	0.75 (0.75)	1.03 (1.09)	1.36 (2.05)
JO	88.7% (67.0%)	106	0.80 (0.80)	1.03 (1.13)	1.26 (1.99)
LH	84.8% (83.3%)	132	0.75 (0.75)	1.01 (1.01)	1.35 (1.36)
LC	80.5% (77.0%)	113	0.66 (0.66)	1.05 (1.06)	1.43 (1.44)
FC	77.9% (75.7%)	140	0.70 (0.70)	0.94 (0.95)	1.30 (1.31)

7.7 Comparison with COM1

In this section, we compare COM2 and COM1 monthly forecasts of the first RMF for each COM1 commodity. As before, COM2 forecasts are constructed from daily data with a 90-day half-life and a Newey-West parameter of 10. COM1 forecasts are derived from monthly returns using a 24-month half-life. We used a common period of 77 months starting with August 2003 until December 2009. We observed that COM2 outperforms COM1 on average for all three measures: Q12(89% vs. 83%), overall bias statistic (1.05 vs. 1.09), and RAD (0.20 vs. 0.26).

Table 7-9. Comparison of COM2 and COM1 monthly forecasts from Aug 2003 to Dec 2009.

name	COM2 Q12	COM1 Q12	COM2 BS	COM1 BS	COM2 RAD	COM1 RAD
CL	95.5% (93.9%)	83.3% (81.8%)	1.00 (1.01)	1.04 (1.07)	0.14 (0.15)	0.22 (0.22)
CO	89.4% (89.4%)	83.3% (81.8%)	1.01 (1.03)	1.03 (1.07)	0.15 (0.17)	0.24 (0.24)
HO	92.4% (92.4%)	87.9% (84.8%)	0.97 (0.97)	0.99 (1.00)	0.16 (0.16)	0.23 (0.23)
GO	92.4% (92.4%)	89.4% (80.3%)	1.05 (1.05)	1.04 (1.06)	0.15 (0.15)	0.25 (0.25)

RB	84.8% (63.6%)	86.4% (69.7%)	1.07 (1.17)	1.04 (1.10)	0.22 (0.31)	0.29 (0.29)
NG	98.5% (87.9%)	93.9% (93.9%)	1.00 (1.04)	0.89 (0.89)	0.16 (0.20)	0.20 (0.20)
SI	87.9% (87.9%)	71.2% (69.7%)	1.11 (1.14)	1.22 (1.25)	0.24 (0.27)	0.29 (0.29)
GC	92.4% (92.4%)	81.8% (80.3%)	1.02 (1.02)	1.16 (1.20)	0.17 (0.17)	0.27 (0.27)
AL	84.8% (84.8%)	81.8% (81.8%)	1.06 (1.06)	1.23 (1.23)	0.18 (0.18)	0.30 (0.30)
CU	93.9% (56.1%)	92.4% (65.2%)	1.13 (1.35)	1.15 (1.28)	0.22 (0.39)	0.32 (0.32)
NI	92.4% (92.4%)	86.4% (86.4%)	1.09 (1.22)	1.14 (1.18)	0.16 (0.20)	0.21 (0.21)
ZI	90.9% (90.9%)	80.3% (71.2%)	1.16 (1.19)	1.27 (1.33)	0.22 (0.24)	0.32 (0.32)
PB	90.9% (83.3%)	71.2% (60.6%)	1.11 (1.17)	1.29 (1.35)	0.24 (0.27)	0.38 (0.38)
W	100.0% (100.0%)	81.8% (81.8%)	0.94 (0.94)	1.19 (1.19)	0.14 (0.14)	0.22 (0.22)
KW	97.0% (95.5%)	81.8% (81.8%)	0.96 (0.97)	1.13 (1.18)	0.17 (0.18)	0.25 (0.25)
C	98.5% (98.5%)	71.2% (66.7%)	1.07 (1.07)	1.24 (1.27)	0.17 (0.17)	0.28 (0.28)
S	80.3% (80.3%)	66.7% (66.7%)	1.18 (1.18)	1.23 (1.23)	0.25 (0.26)	0.33 (0.33)
SB	69.7% (69.7%)	66.7% (66.7%)	1.06 (1.07)	1.02 (1.04)	0.31 (0.31)	0.30 (0.30)
KC	71.2% (71.2%)	97.0% (97.0%)	1.09 (1.10)	0.96 (0.96)	0.30 (0.31)	0.25 (0.25)
CC	84.8% (84.8%)	71.2% (71.2%)	0.99 (0.99)	0.95 (0.95)	0.23 (0.23)	0.28 (0.28)
CT	84.8% (84.8%)	72.7% (72.7%)	1.04 (1.04)	1.05 (1.05)	0.25 (0.25)	0.31 (0.31)
LC	83.3% (83.3%)	92.4% (86.4%)	1.04 (1.07)	0.98 (1.11)	0.27 (0.28)	0.26 (0.26)
FC	97.0% (89.4%)	92.4% (92.4%)	1.03 (1.05)	1.05 (1.15)	0.16 (0.17)	0.17 (0.17)
LH	93.9% (93.9%)	97.0% (97.0%)	1.02 (1.02)	0.96 (0.96)	0.18 (0.18)	0.18 (0.18)

8 Conclusion

The new and enhanced Barra Commodity Model, COM2, introduced in this paper has significant advantages over the model used in previous versions of BIM.

We have increased the number of commodities in the model, reflecting the broadening of this asset class. The precious metals sector adds palladium, platinum, and industrial metals (New York copper and tin), while agricultural commodities expand with the addition of soybean oil, soybean meal, spring wheat, Robusta coffee, London white sugar, and orange juice.

We have increased the estimation frequency from monthly to daily, which results in more responsive and accurate risk forecasts. This enables the use of the commodity model for short-term forecasts, such as value at risk, using the BIM daily model.

With the increased resolution comes the danger of using stale data. We have carefully constructed dynamic investable portfolios called Rolling Maturity Futures that are used as the estimation universe in COM2. Based on open interest data, RMFs reflect the traded part of a commodity curve and alleviate liquidity issues. In addition, they serve as benchmarks of commodity investments along the term structure in the same way traditional commodity indices benchmark commodity investments in the front part of the curve.

The total risk forecast is now split into common and specific components. The common risk is driven by a correlated set of factors whose number depends on the data available for each commodity. The increased number of risk factors (from a single factor per commodity in the previously available model) enables more accurate risk forecasts along the term structure. For many commodities, adding specific risk increases the risk forecast accuracy of long-short portfolios.

As part of BIM301, COM2 will improve the risk forecasts of multi-asset class portfolios by better representing the complex relationships between commodities and other major asset classes. COM2 forecasts are updated daily, enabling risk managers to evaluate risk in a timely manner during turbulent market periods.

Overall, the model provides sufficient coverage and high accuracy in the bias tests we performed, making COM2 an important tool for risk management of commodity investments.

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A. Appendix: Tables and Figures

Table A-1. COM2 Commodities.

Code	**Commodity**	**Exchange**	**Sector**	**In COM1?**
CL	Crude Oil	NYMEX	Energy	Yes
CO	Brent Crude	ICE	Energy	Yes
RB	Gasoline	NYMEX	Energy	Yes
HO	Heating Oil	NYMEX	Energy	Yes
GO	Gas Oil	ICE	Energy	Yes
NG	Natural Gas	NYMEX	Energy	Yes
GC	Gold	COMEX	Precious Metals	Yes
SI	Silver	COMEX	Precious Metals	Yes
PA	Palladium	NYMEX	Precious Metals	No
PL	Platinum	NYMEX	Precious Metals	No
HG	Copper	COMEX	Industrial Metals	No
AL	Aluminum	LME	Industrial Metals	Yes
CU	Copper	LME	Industrial Metals	Yes
NI	Nickel	LME	Industrial Metals	Yes
PB	Lead	LME	Industrial Metals	Yes
SN	Tin	LME	Industrial Metals	No
ZI	Zinc	LME	Industrial Metals	Yes
CT	Cotton	NYBOT	Agriculture	Yes
C	Corn	CBOT	Agriculture	Yes
S	Soybeans	CBOT	Agriculture	Yes
SM	Soybean Meal	CBOT	Agriculture	No
BO	Soybean Oil	CBOT	Agriculture	No
W	Wheat	CBOT	Agriculture	Yes
KW	Winter Wheat	KCBOT	Agriculture	Yes
MW	Spring Wheat	MGE	Agriculture	No
CC	Cocoa	NYBOT	Agriculture	Yes
KC	Coffee	NYBOT	Agriculture	Yes
CF	Robusta Coffee	LIFFE	Agriculture	No
SB	Sugar	NYBOT	Agriculture	Yes
QW	White Sugar	LIFFE	Agriculture	No
JO	Orange Juice	NYBOT	Agriculture	No
LH	Lean Hogs	CME	Livestock	Yes
LC	Live Cattle	CME	Livestock	Yes
FC	Feeder Cattle	CME	Livestock	Yes

Table A-2. Rolling Maturity Future Template for Gold.

date	RMF01	RMF02	RMF03	RMF04	RMF05	RMF06	RMF07	RMF08	RMF09	RMF10
Jan 1, 2009	Apr-09	Jun-09	Aug-09	Dec-09	Feb-10	Jun-10	Dec-10	Jun-11	Dec-11	Jun-12
Feb 1, 2009	Apr-09	Jun-09	Aug-09	Dec-09	Feb-10	Jun-10	Dec-10	Jun-11	Dec-11	Jun-12
Mar 1, 2009	Jun-09	Aug-09	Oct-09	Dec-09	Feb-10	Jun-10	Dec-10	Jun-11	Dec-11	Jun-12
Apr 1, 2009	Jun-09	Aug-09	Oct-09	Dec-09	Feb-10	Jun-10	Dec-10	Jun-11	Dec-11	Jun-12
May 1, 2009	Aug-09	Oct-09	Dec-09	Feb-10	Apr-10	Jun-10	Dec-10	Jun-11	Dec-11	Jun-12
Jun 1, 2009	Aug-09	Dec-09	Feb-10	Apr-10	Jun-10	Dec-10	Jun-11	Dec-11	Jun-12	Dec-12
Jul 1, 2009	Dec-09	Feb-10	Apr-10	Jun-10	Aug-10	Dec-10	Jun-11	Dec-11	Jun-12	Dec-12
Aug 1, 2009	Dec-09	Feb-10	Apr-10	Jun-10	Aug-10	Dec-10	Jun-11	Dec-11	Jun-12	Dec-12
Sep 1, 2009	Dec-09	Feb-10	Apr-10	Jun-10	Aug-10	Dec-10	Jun-11	Dec-11	Jun-12	Dec-12
Oct 1, 2009	Dec-09	Feb-10	Apr-10	Jun-10	Aug-10	Dec-10	Jun-11	Dec-11	Jun-12	Dec-12
Nov 1, 2009	Feb-10	Apr-10	Jun-10	Aug-10	Dec-10	Feb-11	Jun-11	Dec-11	Jun-12	Dec-12
Dec 1, 2009	Feb-10	Apr-10	Jun-10	Aug-10	Dec-10	Feb-11	Jun-11	Dec-11	Jun-12	Dec-12

Table A-3. Historical distribution of open interest for Gold (GC).

date	RMF01	RMF02	RMF03	RMF04	RMF05	RMF06	RMF07	RMF08	RMF09	RMF10
Jan 1, 2009	26.3%	9.0%	1.9%	7.9%	1.0%	2.1%	2.4%	0.8%	1.1%	0.2%
Feb 1, 2009	64.4%	11.2%	2.2%	8.7%	1.3%	2.3%	2.5%	0.8%	1.2%	0.2%
Mar 1, 2009	31.4%	2.8%	4.1%	9.2%	1.6%	2.2%	2.3%	0.8%	1.1%	0.3%
Apr 1, 2009	69.3%	4.8%	4.4%	9.9%	1.9%	2.6%	2.3%	0.9%	1.0%	0.3%
May 1, 2009	23.1%	4.6%	11.4%	2.4%	1.6%	3.0%	2.7%	1.1%	1.1%	0.4%
Jun 1, 2009	62.2%	14.2%	3.1%	2.0%	3.9%	4.2%	1.2%	1.3%	0.7%	1.0%
Jul 1, 2009	33.1%	3.3%	2.6%	4.2%	0.5%	4.3%	1.4%	1.2%	0.9%	0.8%
Aug 1, 2009	67.5%	4.3%	2.7%	4.5%	0.9%	4.4%	1.6%	1.3%	0.9%	0.7%
Sep 1, 2009	68.3%	5.2%	2.4%	4.6%	1.3%	4.8%	1.6%	1.3%	0.9%	0.6%
Oct 1, 2009	68.0%	7.8%	3.0%	4.6%	1.7%	5.1%	1.6%	1.7%	1.0%	0.7%
Nov 1, 2009	28.4%	4.8%	5.8%	1.8%	6.0%	2.0%	1.5%	2.2%	0.8%	0.8%
Dec 1, 2009	61.8%	8.1%	7.9%	2.5%	6.9%	2.2%	1.7%	2.5%	0.8%	0.9%

B. Appendix: RMF Template Construction

The first step to construct an RMF Template is the selection of the incoming candidate contracts for each calendar month. For each calendar month, we do the following:

1. Calculate distribution of open interest (OI) for each contract in the preceding three years.
2. Filter out contracts with percentage of open interest below a given threshold.
3. Filter out contracts which encounter expiry, Last Trade Date or First Notice Day prior to completion of the following month's rolling period.

The result is a table that lists candidate contracts for each calendar month. It is helpful to construct such a table for at least 24 calendar months. The desired threshold is 1%, but sometimes it is helpful to start the construction with a table with a threshold of 0.1% or even smaller.

The second step is to produce the RMF Template by lining up the candidate contracts in columns representing the Rolling Maturity Futures portfolios subject to the following guidelines:

1. The total percentage of open interest captured by the RMF should exceed 40% in any given calendar month, while the average of the total percentage across calendar months should exceed 70%.
2. The Rolling Maturity Futures contracts have a fairly constant three-year-trailing percentage of open interest across calendar months.
3. Rolling occurs only from shorter to longer expiries.
4. Minimize rolling.
5. In certain cases like gold, we use the rule that the first rolling maturity future has to have the highest open interest; therefore, candidate contracts closer to expiration are dropped from consideration. For example, for Gold the most active contract in July is the nearby December, so the nearby October is dropped from the list. In this case, with August the outgoing contract and September and November illiquid, the incoming contract becomes December.
6. The resulting template has annual periodicity in that for a given calendar month the RMFs have the same constituents across the three years.

In Table B-1 we provide a summary of the RMF Templates, including the number of RMFs for each commodity, the percentage of open interest captured and the starting date.

Table B-1. RMF Templates Summary.

name	#RMF	%OI	start date		name	#RMF	%OI	start date
CL	29	83.9%	Apr 28, 1995		CT	7	90.1%	Jun 30, 1995
CO	14	86.1%	Apr 29, 1994		C	5	83.9%	Dec 31, 1991
RB	9	80.5%	Jul 31, 1995		S	6	80.8%	Dec 31, 1991
HO	14	78.4%	Dec 31, 1991		SM	9	85.3%	Dec 31, 1991
GO	11	62.7%	Mar 31, 1993		BO	7	81.5%	Dec 31, 1991
NG	37	84.1%	Apr 30, 1996		W	5	87.7%	Dec 31, 1991
GC	10	76.3%	Dec 31, 1991		KW	5	87.3%	Dec 31, 1991
SI	8	78.7%	Oct 30, 1992		MW	6	88.5%	Apr 30, 1996

PA	2	77.2%	Dec 31, 1991		CC	6	88.6%	Dec 31, 1991
PL	2	78.0%	Dec 31, 1991		KC	8	89.8%	Dec 31, 1991
HG	8	73.3%	Dec 31, 1991		CF	4	86.8%	Dec 31, 1991
AL	30	NA	Jun 28, 2002		SB	4	85.3%	Dec 31, 1991
CU	30	NA	Jun 28, 2002		QW	6	91.3%	Dec 31, 1991
NI	15	NA	Jun 28, 2002		JO	7	80.6%	Dec 31, 1991
PB	15	NA	Jun 28, 2002		LH	6	77.0%	Dec 31, 1991
SN	12	NA	Jun 28, 2002		LC	5	80.6%	Dec 31, 1991
ZI	15	NA	Jun 28, 2002		FC	5	67.2%	Dec 31, 1991

C. Appendix: RMF Calculation

This appendix provides details of the calculation of the three types of RMF indices: price index, excess return and total return.

The RMF Price Index, $RMFPI_i$, for the i^th^ business day of the month is given by

$$RMFPI_i = w_{i1}\, F_{i1} + \; w_{i2}\, F_{i2}$$

where

$$w_{i1} = \begin{cases} 1, \; i < 5 \\ \frac{9-i}{5}, 5 \leq i \leq 9, w_{i2} = 1 - w_{i1} \\ 0, \; i > 9 \end{cases}$$

are the weights of the outgoing and the incoming futures contracts, while F_{i1} and F_{i2} are the futures prices.

To compute the excess return ER_i for i^{th} business day of the month use

$$ER_i = w_{i-1,1}\, R_{i1} + \; w_{i-1,2}\, R_{i2},$$

where

$$R_{ij} = (F_{ij} - F_{i-1,j})/F_{i-1,j},$$

are the simple returns of the outgoing and incoming futures contracts for i^{th} business day of the month. Now, the RMF Excess Return Index level $RMFER_i$ for i^{th} business day of the month is

$$RMFER_i = RMFER_{i-1} * (1 + ER_i).$$

Let the Treasury Bill Return (TBR_i) on any calendar day i be the daily return from a 91-day Treasury Bill. To compute the total return TR_i for i^{th} business day of the month use

$$TR_i = (1 + ER_i + TBR_i) * (1 + TBR_i)^d - 1,$$

where d is the number of non-business calendar days since the business day immediately preceding the i^{th} business day of the month. Now, the RMF Total Return Index level $RMFTR_i$ for i^{th} business day of the month is

$$RMFTR_i = RMFTR_{i-1} * (1 + TR_i).$$

D. Appendix: COM2 Exposures Past and Future

In the estimation period, the number of COM2 exposures is equal to the number of RMFs in existence. Due to a reduced number of RMFs in the past, these fixed exposures may become more collinear, which could negatively impact factor estimation. In the future, there may be newly added RMFs for which exposures need to be calculated.

Conditioning of Exposures

Factor returns are computed by solving numerically the following linear system:

$$X_t^T X_t f_t = X_t^T r_t$$

where X_t^T is the transpose of the exposure matrix. Stability of regression requires that this matrix be well-conditioned, i.e., the condition number be of order 1, and equal to the ratio between the largest and smallest eigen value of the matrix. In the estimation period this happens automatically due to the selection of orthogonal exposures; in this case $X_t^T X_t$ is diagonal and the condition number is equal to 1. In the early part of the model history, however, where not all RMFs exist, the exposures are no longer orthogonal, and the condition number can deviate from 1.

Care has been taken to ensure that the condition number does not exceed five for all commodities.

Extending Exposures

Liquidity in futures contracts changes with time. To accommodate changing market conditions, exchanges may offer an increased number of maturities for trading. For example, in October 2008, the London Metal Exchange increased the traded Aluminum monthly maturities by five years. Similarly, in December 2001, NYMEX increased the traded Natural Gas monthly maturities by three years.

COM2 accommodates such events by adding RMFs with longer maturities, thus preserving the model forecasting ability in the back end of the curve.

What are the exposures of newly added RMFs? Re-estimating exposures using a new estimation period may change existing exposures and may introduce twist exposures in the back end with high absolute values which are unrealistic.

To solve this problem we model the shapes using exponentials. To model shift and twist exposures, we find a least squares fit of the form

$$X(\tau) = a + b\, e^{-c\,\tau}$$

with $X(\tau_1) = 1$, where τ_1 is the first RMF maturity. In addition, the parameter a represents very long-maturity exposures and is at our disposal to prescribe, thus reducing the number of parameters to 1.

In order to model butterfly exposures, another exponential is needed:

$$X(\tau) = a + b\, e^{-c\,\tau} + b_2\, e^{-c_2\tau}$$

This methodology was applied to five of the six LME metals, for which the number of RMFs increased by two or three during the estimation period. Their exposures were determined in two steps. First, the PCA procedure was used to determine the exposures for the subset of RMFs excluding the newly-added RMFs. Second, exposures were extended using the modeling approach described above.

E. Appendix: More on Forecasting Spread Risk

In this appendix, we provide additional details on the forecasting performance for RMF spreads described in section 7.5. First, we compare the forecasting performance with and without specific risk. The graphs below show the difference in the Q12-statistic. Positive values correspond to better forecasting when using the specific risk model. Notice that for most of the metals, and crude oil and natural gas, excluding specific risk helps, while for agricultural and livestock commodities the evidence is against.

Figure E-1. COM2 with and without specific risk for RMF spreads (energy and metals).

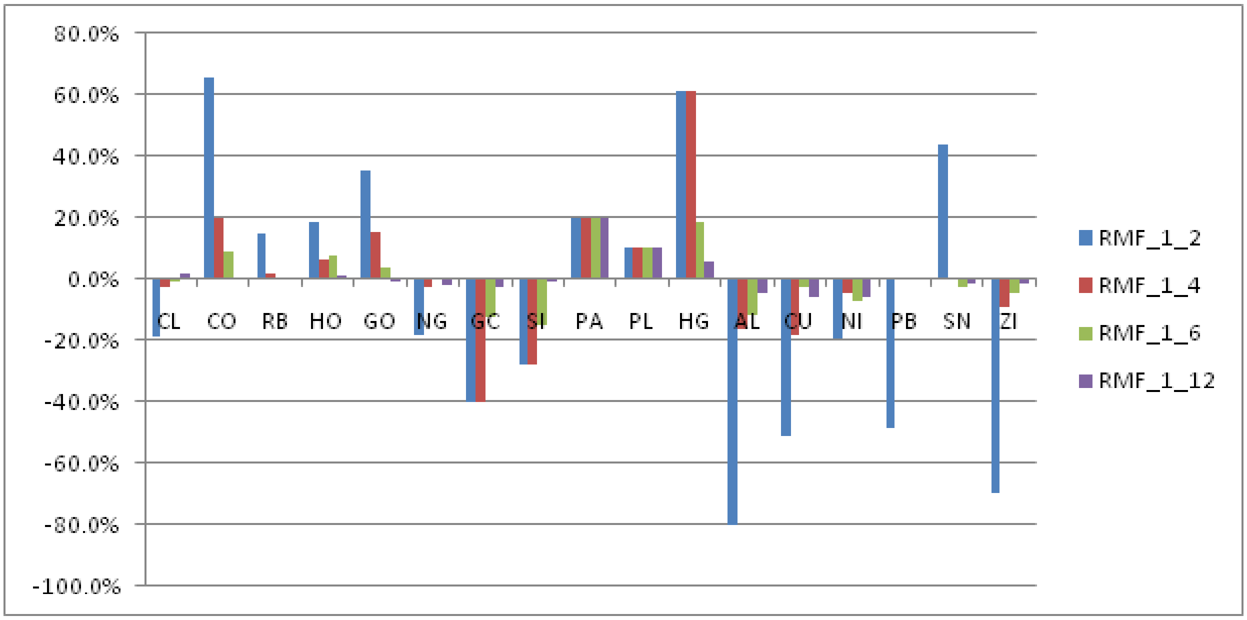
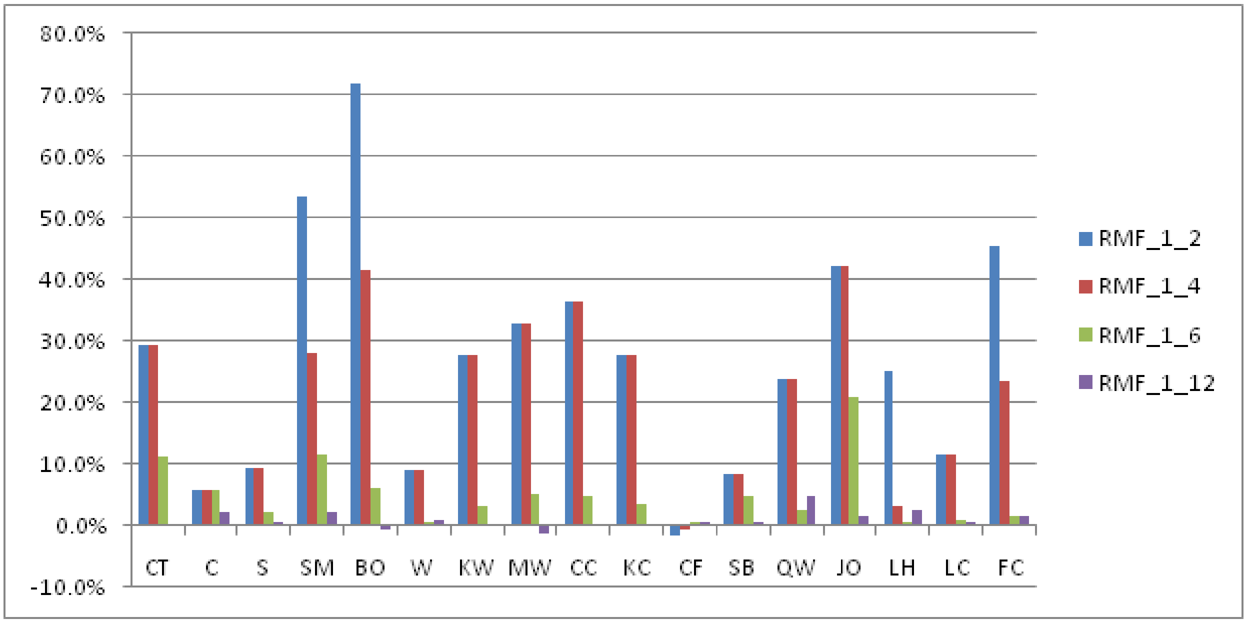


Figure E-2. COM2 with and without specific risk for RMF spreads (agriculture and livestock)



Next, we compare COM2 forecasting performance with that of simple EWMA model for the same four spreads and for each commodity. The tables below graph the difference in the Q12-statistic, with positive values equivalent to a COM2 advantage. Generally, the EWMA advantage decreases with increasing spread.

Figure E-3. COM2 vs. EWMA for RMF spreads (energy and metals).

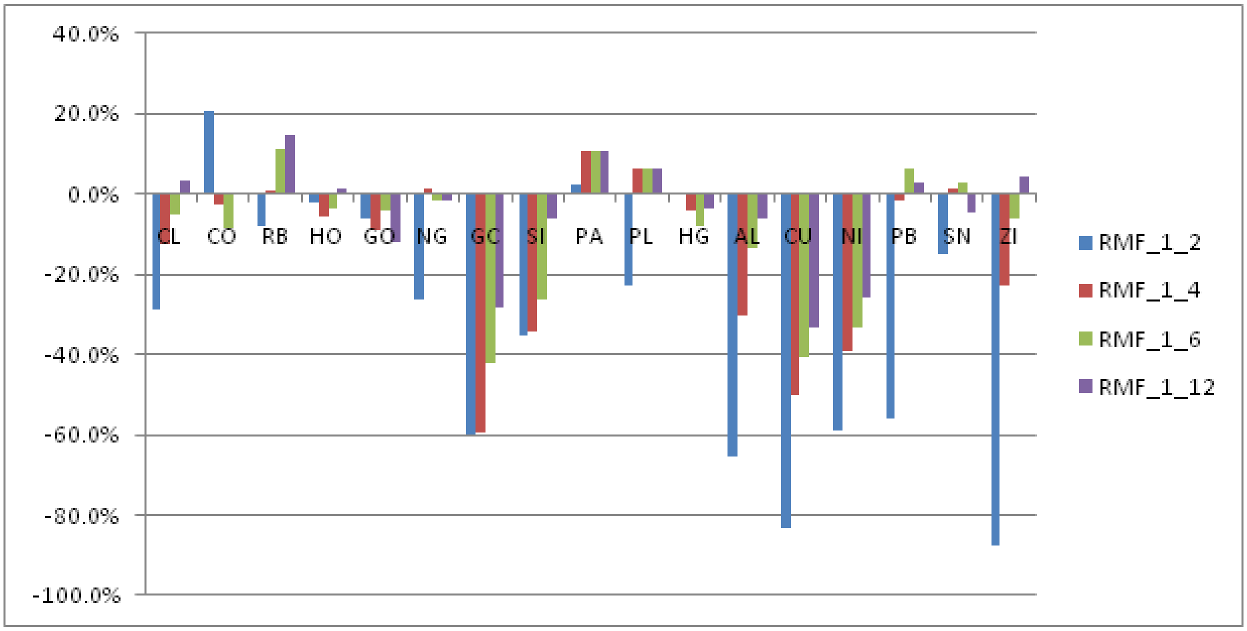
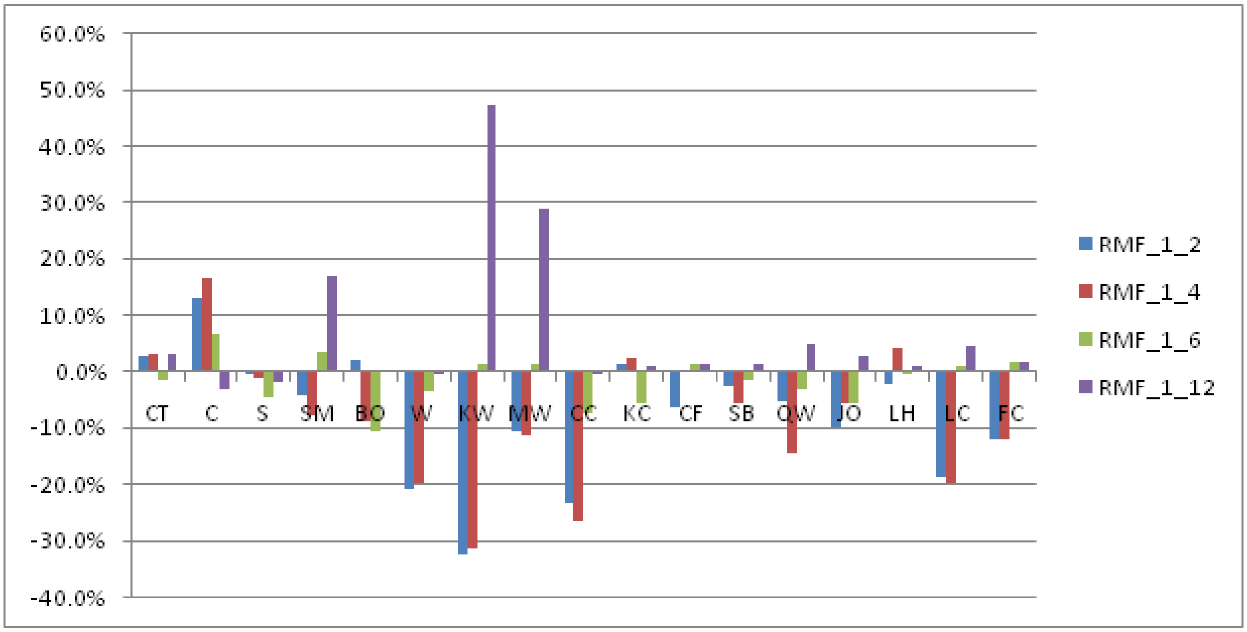


Figure E-4. COM2 vs. EWMA for RMF spreads (agriculture and livestock).



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