STRATEGIC AND TACTICAL ROLES OF ENHANCED COMMODITY INDICES

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Abstract

This article formally compares two traditional long-only commodity indices, S&P-GSCI and DJ-UBSCI, with their enhanced versions that exploit signals based on contract maturity, momentum and term structure. The enhanced indices are found to be useful for tactical asset allocation. With alphas ranging from 2.77% to 5.49% per annum, the maturity-enhanced indices offer the best abnormal performance after accounting for liquidity risk. Momentum and term structure enhancements also earn a positive, albeit smaller, alpha of 1.97% per annum on average. All the enhanced indices are found to be as effective tools for risk diversification and inflation hedging as their traditional counterparts, making them useful for strategic asset allocation.

Keywords: Long-only commodity indices; Time-to-maturity; Momentum; Term structure.
JEL classification codes: G13, G14.

INTRODUCTION

Indices are regarded as the simplest and most cost-efficient way to acquire exposure to underlying markets. In commodity markets the first index dates from 1957 and was created by the Commodity Research Bureau as a broad indicator of commodity price movements. Many other indices followed such as the Standard & Poor's Goldman Sachs Commodity Index (S&P-GSCI) and the Dow Jones-UBS Commodity Index (DJ-UBSCI, formerly known as DJ-AIGCI). The *traditional* or first-generation indices tend to hold the most active contracts and promise a passive, long-only exposure to commodities. These indices have often been cast as suboptimal because they are long-only, rebalance infrequently and fail to take into account the term structure of commodity prices. To remedy these problems, a range of *enhanced* or second-generation indices[1] has emerged with novel features such as exploiting market signals influential to commodities (such as momentum), changing allocation more frequently or explicitly accounting for the propensity of commodity futures markets to be either contangoed or backwardated.

Buying commodity indices can be seen as portfolio strategies but given the proliferation of customized indices it has become increasingly challenging for investors to discriminate between them. This is largely because complex technical specifications can obscure their risk profile and because their characteristics vary greatly from one index to another (*e.g.* constituents, allocations, rolling techniques, diversification constraints and weighting schemes). To assist investors in this endeavor, our paper extends past research by offering a formal comparative analysis of two popular first-generation indices (S&P-GSCI and DJ-UBSCI) and their second-generation

[1] To cite only a few, the following enhanced indices are open to investment at the time of writing this paper: Bache Commodity Index, Barclays Commodity Index, Credit Suisse Commodity Benchmark Index, Deutsche Bank Liquid Commodity Index, Diapason Commodity Index, DCI BNP Paribas Enhanced Index, JPMorgan Commodity Index, Merrill Lynch Commodity Index, MorningStar Commodity Index, UBS Bloomberg Constant Maturity Commodity Index. For detailed information on some of these indices, see Kazemi, Schneeweis & Spurgin (2008).

counterparts that exploit signals based either on contract maturity, momentum, or term structure. In so doing, the implicit goal is to test whether second-generation (enhanced) indices meet the twofold objective, often claimed by index providers, of matching the risk exposure to commodity markets of first-generation (traditional) indices while offering better performance to investors.

The paper contributes to the literature in three directions. First, it tests whether the performance of the first-generation S&P-GSCI and DJ-UBSCI can be enhanced by rolling to mid- to far-end contracts as opposed to front ones. Although maturity signals are not entirely new to practitioners, there is lack of empirical evidence on the liquidity-adjusted performance of maturity-enhanced indices. Our paper seeks to fill this gap by formally testing, via a commodity-based liquidity risk premium à la Pastor and Stambaugh (2003), whether the observed outperformance is merely compensation for the less liquid distant contracts. This differentiates our paper from Mouakhar & Roberge's (2010) study where passive commodity portfolios that optimize roll yield are deployed but liquidity risk is not explicitly accounted for. Other important differences relate to our focus on enhancing the traditional S&P-GSCI and DJ-UBSCI and to the fact that we run a 'contest' between momentum, term structure and maturity signals for passive commodity investors, while Mouakhar & Roberge's (2010) main focus is optimizing the roll yield.

The second contribution is quantifying the return enhancement that can be earned from exploiting momentum and/or term structure signals in a long-only framework. The extant commodity literature has analyzed momentum and term structure strategies[2] in long-short settings. Thus there remains the question of whether the performance of the S&P-GSCI and DJ-UBSCI can be enhanced by exploiting momentum and/or term structure signals in a long-only

[2] Erb & Harvey (2006), Gorton & Rouwenhorst (2006), Miffre & Rallis (2007), Shen, Szakmary & Sharma (2007), Fuertes, Miffre & Rallis (2010) and Szakmary, Shen & Sharma (2010) show that long-short strategies based on momentum, roll-returns or a mix of both signals can yield abnormal returns. Other contributions such as Jensen, Johnson & Mercer (2002) and Vrugt, Bauer, Molenaar & Steenkamp (2007) highlight the role of fundamental information in forecasting commodity returns.

context too. This issue is of paramount importance to asset managers with long-only mandates. As a byproduct, we run a horse race across all three signals (maturity, momentum and term structure) in order to provide investors with formal empirical evidence on their relative merits.

The final contribution is to test whether the superior returns afforded by enhanced indices come at the cost of losing the strategic roles of commodities; namely, their risk diversification and inflation hedge properties. Given that long-short commodity portfolios have been shown to be poor inflation hedges (Miffre & Rallis, 2007; Basu & Miffre, 2012), this question is non-trivial.

To preview our key findings, we demonstrate empirically that long-only enhanced versions of the S&P-GSCI and DJ-UBSCI are valuable for both tactical and strategic asset allocations. The enhanced indices generate alphas ranging from 1.34% to 5.49% a year and thus are useful tactical bets. The time-to-maturity of the contracts stands out as the most profitable signal among those examined. The index-enhancement that targets distant maturities of up to 12 months generates an alpha of 4.85% on average. This outperformance is not merely driven by the lower liquidity of distant contracts. Our findings suggest that the enhanced indices retain the risk diversification and inflation hedging properties of the traditional S&P-GSCI and DJ-UBSCI documented by Bodie & Rosansky (1980), Bodie (1983) and Erb & Harvey (2006) *inter alios*. They are thus as useful strategic asset allocation tools as are the traditional ones.

The rest of this article is organized as follows. The data are described next. Afterwards we discuss the methodology and empirical findings on the performance of enhanced S&P-GSCI and DJ-UBSCI versions. We then compare the strategic roles of traditional and enhanced indices by focusing on their ability to diversity risk and hedge inflation shocks. A final section concludes.

DATA

The S&P-GSCI is a production-weighted index of the prices of exchange-traded, liquid, physical commodity futures contracts with a heavy skew towards the petroleum sector. The DJ-UBSCI is both a liquidity and production-weighted index of the prices of exchange-traded, physical commodity futures contracts. The two indices were officially launched in July 1992 and July 1998, respectively, but their performance has been backfilled to January 1969 (S&P-GSCI) and to January 1991 (DJ-UBSCI). The choice of starting date for the observations is dictated by data availability. To ensure accurate tracking, daily data are required on *all* the index constituents and, as a result, our empirical analysis begins on October 24, 1988 for the S&P-GSCI and on January 4, 1991 for the DJ-UBSCI.[3] November 20, 2008 marks the sample end in both cases.

The dataset from *Bloomberg* comprises, for all available maturities, daily (dead and live) futures prices of all the commodities that form the S&P-GSCI and the DJ-UBSCI, and daily prices of the two indices.[4] We employ closing prices of the contracts traded on the London Mercantile Exchange (LME) − aluminum, copper, lead, nickel, tin and zinc – expiring on the 3rd Wednesday of each month. Prior to December 2000, most of the LME futures did not exist, thus

[3] The samples for the S&P-GSCI and DJ-UBSCI are allowed to begin at different time points because the purpose of the paper is not to conduct between-index comparisons (*i.e.* distinctions between the two indices) but instead to conduct within-index comparisons (*e.g.* the tactical/strategic roles of the enhanced versus traditional S&P-GSCI). Accordingly, we exploit as much data as is available on each index at the time of writing up instead of constraining the analysis to a shorter but common time span. Nevertheless, as a robustness check we repeated the main analysis of the S&P-GSCI using January 4, 1991, as starting date thus making it common to both indices. The main qualitative findings regarding the superiority of the enhanced S&P-GSCI vis-à-vis the traditional counterpart and their strategic asset allocation roles remain unchallenged. This is to be expected since the shorter and longer samples for the S&P-GSCI differ in less than 3 years (11% of total observations) which do not represent a particularly anomalous period. Detailed results are available from the authors upon request.

[4] The indices are available on both an excess return and total return form. The excess return indices reflect the return of underlying commodity futures price movements only, whereas the total return indices represent the return of fully-collateralized futures positions. In line with previous research, we have not included the return of the collateral in our analysis. For expositional simplicity, the term "return" throughout the paper refers to the excess return of traditional and enhanced indices.

in order to replicate the indices we use for these commodities daily forward contracts with fixed maturities which are available from *Bloomberg*.

The index constituents and starting dates are listed in Table I. The table also includes information on rolling schedules and on the exchanges where the contracts were traded at the time of writing this article. We start by carrying out a replication of the first-generation indices following the methodology in the index providers' handbooks; see S&P-GSCI (2007) and DJ-AIGCI (2006).[5] The statistics reported in Appendix A bear out a successful replication exercise.[6]

[Table I around here]

MATURITY-ENHANCED INDICES

Providers of first-generation indices typically roll positions from the front to the second contract on pre-defined schedules. This methodology, however, does not take into account the shape of the term structure of commodity prices nor the fact that the volatility of forward prices rises as contracts approach maturity (Samuelson, 1965; Daal, Farhat & Wei, 2006). Consequently, traditional indices can exhibit significant roll-losses, extreme volatility and returns that can differ substantially from commodity spot returns. This section presents a formal investigation of the conjecture that maturity signals can enhance the performance of traditional indices and that the outperformance is not merely a compensation for the lesser liquidity of distant contracts.

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[5] At the start of the expiration month, futures contracts that are expiring are rolled (exchanged) for contracts with the next applicable expiration month as detailed in Table I, columns 5 and 6. The roll-period lasts 5 days and occurs on the 5th through the 9th business day of the month for the S&P-GSCI (6th-10th for the DJ-UBSCI) at a rate of 20% per day dollar-weighted. The indices are replicated by combining the yearly weights provided by the index providers with the daily returns of the index constituents.

[6] To name a few, the S&P-GSCI and the replicating portfolio have identical annualized geometric means and the difference between their annualized arithmetic means is negligible. The S&P-GSCI and replicating portfolio have also similar Sharpe ratios. In terms of risk, the annualized volatility of the replicating portfolio, skewness, kurtosis and 99% VaR are undistinguishable from those of the S&P-GSCI. The correlation between the mimicking portfolio and the S&P-GSCI at 0.9992 is insignificantly different from unity. Likewise for the DJ-UBSCI.

Methodology

Instead of rolling the constituents as in the traditional S&P-GSCI and DJ-UBSCI methodologies, the idea is to roll into the specific contracts in the term structure of each constituent that give us an average maturity (expiration) of either 3, 6, 9 or 12 months. Taking aluminum as an example, the 3-month maturity S&P-GSCI spends 69% of the time on the third contract and 31% of the time on the fourth, on average over the whole sample. As a result, its average time-to-maturity is 2.83 months. Similarly, the 6-month S&P-GSCI targets 6-month maturity contracts. In the case of aluminum, this implies holding an investment with an average time-to-maturity of 5.82 months, spending 69% of the time on the 6th month contract and the remaining 31% on the 7th month contract. For some commodities, it is simply unfeasible to hold contracts very far inside the term structure either because these contracts do not exist at all or because they did not exist at some point in the sample period. However, in order to match the first-generation indices, we keep those commodities by focusing on the contracts that are the closest to the target maturity.

It is important to note that, since our main purpose is to isolate the impact of *time-to-maturity* on index performance, the weight allocated to a given commodity in the enhanced index is identical to that used by first-generation index providers. Hence, the first-generation indices and maturity-enhanced ones differ only regarding the specific location on the term structure of the contracts and not regarding the weight assigned to each of the contracts.

Performance and Risk Profile of Maturity-Enhanced Indices

Table II, Panel A summarizes the performance of first-generation and maturity-enhanced indices for 3, 6, 9 and 12-month target maturities. The findings indicate that contract maturity and index performance are positively related. The annualized mean return in Panel A for the first-generation S&P-GSCI (referred to as "Index") is 3.68% and increases noticeably for the maturity-enhanced

S&P-GSCI to levels between 8.66% (3-month) and 8.83% (12-month). Likewise, the mean return rises monotonically with contract maturity from 1.97% for the first-generation DJ-UBSCI to 6.29% for its 12-month counterpart. The spreads between the maturity-enhanced and first-generation indices in Panel B are economically and statistically significant. Similarly, the annualized alphas of the enhanced indices relative to the first-generation ones tend to increase with contract maturity, ranging from 5.15% (3-month) to 6.18% (12-month) for the S&P-GSCI and from 2.99% (3-month) to 4.72% (12-month) for the DJ-UBSCI. All 8 alphas are clearly significant both statistically (1% level) and economically, averaging at 4.93%.[7] The Sharpe ratios of the enhanced indices also rise with maturity, ranging from 0.3595 to 0.5753, and thus compare favorably to those of the S&P-GSCI and DJ-UBSCI at 0.1543 on average. The 12-month index offers the best performance as borne out by a Sharpe ratio about 4 times larger than that of the original indices, and strong alphas of 6.18% (S&P-GSCI) and 4.72% (DJ-UBSCI) per annum.

[Table II around here]

The tracking error of the maturity-enhanced indices (4.50% a year on average) and their betas relative to first-generation indices average out at 0.7838. Both aspects, non-zero tracking error and deviation of betas from 1, can be seen are the prices to pay for improved performance.[8] However, any tracking error below 10% is typically considered acceptable; see *e.g.* Mouakhar & Roberge (2010). The pairwise correlations between the returns of the maturity-enhanced and first-

[7] The residuals of each regression were subjected to the Breusch-Godfrey LM autocorrelation test and Engle LM heteroskedasticity test (both for a maximum lag order of 12). The residuals generally have white noise properties but in a few cases there is evidence of autocorrelation and/or heteroskedasticity. Hence, the significance *t*-ratios are based on either the usual OLS standard errors, heteroskedasticity-robust (White) ones or autocorrelation- and heteroskedasticity-robust (Newey-West) ones, as appropriate.

[8] Investors in index trackers are first and foremost interested in the ability of the tracker to mimic the ups and downs of the underlying index. The lower the tracking error and the closer the tracker's beta (relative to the index) is to unity, the better the ability of the tracker to passively mimic the index; see Elton, Gruber & Busse (2004) for index funds or Elton, Gruber, Comer & Li (2002) for exchange traded funds. Tracking errors are measured as the annualized standard deviation of the residuals from a regression of the mimicking portfolio returns on the original index returns; *e.g.* see Pope & Yadav (1994).

generation indices are very high (in the ballpark figure of 95%) and statistically undistinguishable from 100%. These properties suggest that the maturity-enhanced indices mimic reasonably well the underlying commodity market, thus lending themselves as appropriate tools for strategic asset allocation (*i.e.* risk diversification and inflation hedging).

Table II, Panel A also illustrates that the volatility of the enhanced indices decreases as target maturity rises. For instance, the annualized standard deviation of returns for the baseline S&P-GSCI stands at 21.26%, while that of the 3-, 6-, 9- and 12-month S&P-GSCI stands at 19.11%, 16.91%, 15.78% and 15.35%, respectively. Similarly, the 99% Cornish-Fisher VaR monotonically becomes more favorable as one moves from the 3-month to the 12-month strategies.[9] These results are consistent with Samuelson's (1965) maturity effect suggesting that the volatility of futures prices increases as contracts approach maturity. However, the maturity-enhanced indices are riskier than the traditional indices in terms of third and fourth moments, namely, they are more negatively skewed and more leptokurtic.[10]

For completeness, we also examine the performance of the individual constituents of the maturity-enhanced indices (listed in Table I) and find that their mean return tends to increase and their volatility to decrease with contract maturity. The most extreme instance is natural gas with

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[9] The 99% VaR (Cornish-Fisher) reported is a downside risk measure representing the monthly loss which is expected to be exceeded only once every one hundred months. Cornish-Fisher VaR takes into account deviations from gaussianity of the returns distribution such as high skewness and leptokurtosis.

[10] The negative skewness of the first-generation and maturity-enhanced indices (also common to other enhanced indices below) might come as a surprise since rises in demand linked to the extraordinary economic growth of emerging markets such as China, wars or weather-related disturbances *inter alios* have a positive impact on prices inducing a longer right tail in the distribution of commodity futures returns (Erb & Harvey, 2006; Gorton & Rouwenhorst, 2006). Further analysis indicated that this negative skewness is an artifact of the very poor index performance over the period July 2008-November 2008 (over those five months, a dramatic fall in commodity prices was observed which can be linked to the slowdown in worldwide real economic activity triggered by the global financial crisis). For instance, for the first-generation S&P-GSCI and DJ-UBSCI the skewness becomes 0.3537 and 0.1990, respectively, if the sample ends in June 2008 instead. We should emphasize, however, that the exclusion of those five months from our analysis has no impact on the overall conclusions of the paper regarding the behavior of enhanced indices. Detailed results are available from the authors upon request.

an annualized differential mean return of 24.77% between the 12-month and front contracts; as maturity increases, the standard deviation of returns decreases from 51.5% (front-end contracts) to 23.1% (12-month contracts). Similar patterns are observed across the term structure for most commodities although not universally. Precious metals are a noteworthy exception as they do not present much differentiation in mean returns and standard deviations along the curve. In the case of copper, a spread in mean return of merely 0.18% a year is found between the 12-month and the front contracts; likewise, the standard deviation of returns decreases very little from 24.5% (front contracts) to 22.1% (12-month contracts). Detailed results for all 30 constituents are unreported, to preserve space, but are available from the authors upon request.

Is the Outperformance of Maturity-Enhanced Indices Driven by Illiquidity?

It is commonly acknowledged that contracts located in the mid- to far-end of the term structure are less liquid than front contracts. This is confirmed empirically in Table III by comparing the average open interests (OI), or the amount of outstanding contracts, of the S&P-GSCI and DJ-UBSCI constituents along their respective term structures.[11] In all but two cases (aluminum and copper), the average OI of the front contracts substantially exceed those of the 3- to 12-month contracts. On average across the commodity spectrum, the OI of the front contracts (at 38,885) doubles that of the 3-month contracts (at 19,282) and the gap widens monotonically along the term structure, becoming 15 times higher than that of the 12-month contracts (at 2,586). As investors demand a premium for holding less liquid assets (Amihud, 2002; Pastor & Stambaugh, 2003), the outperformance of maturity-enhanced indices identified in Table II could be merely a compensation for taking on additional liquidity risk.

[11] Monthly OI observations are available from *Datastream* for most of the constituents listed in Table I. The exceptions are copper NYMEX, lead, nickel, tin and zinc. The reported average OIs are for the time period from January 1991 to November 2008.

[Table III around here]

We test this conjecture empirically via a two-factor model by regressing the returns of each maturity-enhanced index on a constant, the returns of the corresponding first-generation index, and a commodity-based liquidity risk premium constructed as in Pastor & Stambaugh (2003).[12] Appendix B provides details of the methodology employed to derive the latter. The regression coefficients, reported in Table IV, reveal three noteworthy aspects. First, the returns of the maturity-enhanced indices are related to liquidity risk in a plausible manner, as borne out by significantly positive liquidity betas that increase monotonically with contract maturity. Second, the index betas in the regressions that include the liquidity risk premium (Table IV) are quite close to those from regressions excluding it in line with the fact that the two factors are orthogonal. For instance, the index beta across maturity-enhancement strategies stands at an average of 0.7926 in Table IV (two-factor model) and at an average of 0.7838 when a single-index model is used (Table II; Panel A). Last but not least, the alphas of the maturity-enhanced indices, irrespective of the strategy considered (3-month to 12-month), remain significant both economically and statistically after controlling for liquidity risk at 5.16% (S&P-GSCI) and 3.71% (DJ-UBSCI) a year on average. They also rise monotonically with maturity. Therefore, although liquidity risk plays a role, as one would expect, it cannot fully account for the outperformance of the maturity-enhanced indices relative to the traditional ones.

[Table IV around here]

In subsequent sections, we investigate in a long-only framework the performance of index-enhancement strategies based on momentum, term structure or a hybrid of both signals. Because traditional asset managers have long-only mandates, this exercise is worthwhile given the vacuum

[12] Previous liquidity risk premium investigations focus on equity and fixed income markets (*e.g.* Amihud, 2002; Pastor & Stambaugh, 2003; Fontaine & Garcia, 2012). To the best of our knowledge, we are the first to replicate the work of Pastor & Stambaugh (2003) in a commodity framework.

of research in this regard; existing commodity studies on momentum and/or term structure solely concentrate on long-short strategies. Therefore it remains to be shown that abnormal performance can be earned by following momentum or/and term structure signals in long-only settings. We first outline the methodology for each index-enhancement and then analyze the resulting risk-return profile. The alphas of momentum- and/or term structure-enhanced indices are measured via the same two-factor model outlined above, treating as risk factors the corresponding first-generation index and the commodity-based liquidity risk premium of Pastor and Stambaugh (2003). This is to maintain consistency throughout the paper.

MOMENTUM-ENHANCED INDICES

Methodology

Following a recent literature that documents momentum effects in commodity futures markets (Erb & Harvey, 2006; Miffre & Rallis, 2007; Shen, Szakmary & Sharma, 2007; Szakmary, Shen & Sharma, 2010), we deploy enhanced versions of the first-generation S&P-GSCI and DJ-UBSCI that exploit price continuation. Accordingly, if a specific constituent performed well (or poorly) relative to its peers in the recent past, it is expected to outperform (underperform) in the near future. Thus the essence of momentum-enhancement strategies is that the weighting of the commodity with the best (worst) past performance is increased (decreased) vis-à-vis its weighting in the traditional index by a larger percentage than the weighting of the commodity with the second best (worst) performance and so forth.

For concreteness, at the start of every roll-date (5^{th} and 6^{th} business day of the maturity month, respectively, for the S&P-GSCI and DJ-UBSCI), we calculate the mean daily return of each constituent over the preceding month. We then rebalance by adjusting the original index weightings (S&P-GSCI or DJ-UBSCI) upwards/downwards for a given constituent if its previous month's performance was above/below the cross-sectional median. Thus the weightings of the best performers (called winners) over the preceding month are adjusted upwards and the weightings of the worst performers (called losers) over the preceding month are adjusted downwards. The resulting long-only portfolio[13] is held for one month at the end of which we update again the weights of the constituents of the momentum-enhanced index to a new value that is derived from the original weights and past performance as formally presented below.

Between roll-dates, weights evolve naturally according to their performance as follows:

$$w_{i,t} = \frac{w_{i,t-1} \times (1 + r_{i,t})}{1 + w_{i,t-1} \times (1 + r_{i,t})}, \; i = 1,..., N \tag{1}$$

whereas on roll-dates weights are specifically adjusted to exploit momentum. Two aspects of our weight adjustment are aimed at making it robust to outliers (*i.e.* infrequent extreme low/high returns). One is the use of the median as measure of central tendency. The other is reliance on the *relative* performance of index constituents.[14] For concreteness, the weights of constituents with below-or-equal-to-median average returns are adjusted on the t roll-date as follows:

$$wadj_{i,t} = wo_{i,t} - \frac{p \times \sum_{i=1}^{m} wo_{i,t} \times (m - position_{i,t} + 1)}{\sum_{i=1}^{m} (m - position_{i,t} + 1)}, \; i = 1,..., m \tag{2}$$

where the subscript i=1 to m (m<N) refers to the constituents that have exhibited mean returns below-or-equal-to-median in the previous month, N is the total number of constituents for each index, t is the roll-date (5th or 6th business day according to the index), $wadj_{i,t}$ is the weighting of

[13] The downward adjustment of each component's weight is naturally limited since in our setting short-selling an index constituent is not possible.

[14] A slightly different weighting scheme based on absolute performance was also deployed for the momentum (and subsequent term structure) strategies giving, by construction, a less gradual weight evolution. But overall the main findings are robust to the weighting method. Detailed results are available.

constituent i after the adjustment on the t roll-date, $wo_{i,t}$ is the original index weighting for the commodity at that roll-date, p is the percentage by which we want the weighting of the below-the-median commodities as a whole to fall (we adopt p= 50%) and $position_{i,t}$ is the ranking of the i^{th} constituent on rolling day t. *Position* takes the value of 1 for the asset with the worst performance, 2 for the second-worst performance asset and so forth.

We adjust first the weightings for all the below-the-median constituents in order to determine the maximum increase in the weights for the contracts with above-the-median performance so that, by construction, the new weights (like the original ones) add up to one. The weights for the constituents with above-the-median performance are then adjusted as follows:

$$wadj_{j,t} = wo_{j,t} + \frac{\left(\sum_{i=1}^{m} wo_{i,t} - \sum_{i=1}^{m} wadj_{i,t}\right) \times \left(N - m - position_{j,t} + 1\right)}{\sum_{j=1}^{N\text{-}m}\left(N - m - position_{j,t} + 1\right)}, \; j = 1,\ldots,N - m \tag{3}$$

where *position* is the asset's performance rank equal to 1 (best), 2 (second-best) and so on.

Performance and Risk Profile of Momentum-Enhanced Indices

Summary statistics for the momentum-enhanced indices are presented in Table V, column 3. Their outperformance, as measured by the spread, on a yearly basis stands at 1.29% (S&P-GSCI) and 1.46% (DJ-UBSCI). Similarly, the Sharpe ratios of the enhanced indices (at 0.2284 on average) are nearly 50% higher than those from the traditional indices (at 0.1543 on average).

[Table V around here]

Momentum enhancement earns average annualized alpha of 1.35% which is moderate in comparison to that from maturity enhancement (c.f. Table IV) and unreliably different from zero but nonetheless economically significant. Also in contrast to the latter, the liquidity betas of the momentum-enhanced indices are negligible which is quite plausible given that they trade the most liquid contracts located at the front-end of the term structure.

The tracking errors of momentum-enhanced indices are low (at about 3.8%) and their betas relative to the underlying indices are insignificantly different from unity. Moreover, the high correlations between the returns of the enhanced and traditional indices at 98.43% (S&P-GSCI) or 96.73% (DJ-UBSCI) are statistically not different from 100%. In terms of volatility, kurtosis and 99% VaR, the risk profile of the indices and enhanced replications are virtually identical; the only exception is the skewness of the enhanced indices which appears favorably less negative. Overall this evidence suggests that momentum-enhanced indices offer outperformance relative to traditional indices while also mimicking quite well the ups and downs of commodity markets.

TERM STRUCTURE-ENHANCED INDICES

Methodology

Backwardation (contango) occurs when the term structure of commodity futures prices is downward-sloping (upward-sloping) which materializes in positive (negative) roll-returns.[15] Erb & Harvey (2006), Gorton & Rouwenhorst (2006) and Fuertes, Miffre & Rallis (2010) show that commodities with high roll-returns tend to outperform commodities with low roll-returns.

[15] Backwardation and contango arise as a result of the imbalance between long and short positions of hedgers which requires the action of speculators to restore equilibrium (*e.g.* see Basu & Miffre, 2012). They can also be linked to inventory considerations according to which contangoed markets exhibit high inventory levels and backwardated markets low ones (*e.g.* see Gorton, Hayashi & Rouwenhorst, 2008). The roll-return is the price gap between distinct-maturity contracts, $R_t=\{\ln(P_{t,1})\text{-}\ \ln(P_{t,2})\}\times 365\ /\ (n_{t,2}\text{-}\ n_{t,1})$, where $P_{t,1}$ is the time t price of the nearest-to-maturity contract, $P_{t,2}$ is the price of the second-nearest contract, $n_{t,1}$ ($n_{t,2}$) is the number of days between time t and the maturity of the nearby contract (second-nearby contract). For example, take crude oil prices on the first day that the term structure-enhanced DJ-UBSCI was constructed (*i.e.* January 31, 1991). On that day, the front contract (with a February 20, 1991 maturity) traded at 21.54US$ per barrel and the second-nearest contract (with a March 20, 1991 maturity) traded at 20.65US$. The roll-return on that day was positive, $R_t = \{\ln(21.54)\text{-}\ln(20.65)\} \times 365\ /\ (48\text{-}20) = 0.55$, as is typical of energy markets that are often in backwardation.

Building on this evidence, we examine the performance of traditional indices enhanced by term structure (TS) signals. Accordingly, on roll-dates we rebalance each constituent's weight upwards (downwards) if its roll-return is above (below-or-equal) the median roll-return. If a constituent is in relatively strong backwardation (*i.e.* it has higher roll-return than its peers), it is expected to perform well in the future, so its weight is adjusted up. Likewise, if a constituent is in relatively strong contango (*i.e.* lower roll-return than that of its peers), it is expected to perform poorly in the future, so its weight is adjusted down.

The corresponding long-only portfolio is held for one month at the end of which the constituents weights are reset to values determined according to the original index weights and the then-prevailing relative roll-returns. More specifically, the weights of constituents with below-or-equal-to-median roll-returns are set as in equation (2) and those of constituents with above-the-median roll-returns are set as in equation (3); the main distinctive aspect of this strategy (versus the momentum one) is that the ranking criterion is the relative roll-return on the roll-date. Again between roll-dates, weights evolve daily according to (1) in a natural fashion.

Performance and Risk Profile of Term Structure-Enhanced Indices

As shown in Table V, column 4, the TS-enhanced indices are effective tools for tactical asset allocation. This is borne out by Sharpe ratios almost twice as high as those of the first-generation indices (column 2) and by economically and statistically significant alphas of 2.28% per annum on average. Liquidity betas undistinguishable from zero suggest that the TS-enhanced indices are not subject to liquidity risk, in line with the fact that they trade liquid front contracts.

The tracking errors of the TS-enhanced indices at 3.81% a year on average are acceptable while the betas of the TS-enhanced indices relative to the first-generation counterparts at 0.9458 (S&P-GSCI) and 1.0054 (DJ-UBSCI) are reliably equal to unity according to *t*-tests. Likewise, the correlations between the original and TS-enhanced indices are very strong at 98.11% (S&P-GSCI) and 97.01% (DJ-UBSCI). The risk measures (volatility, skewness, kurtosis and 99% VaR) obtained for both types of indices, original and enhanced, are nearly identical. Overall the TS-enhanced indices are shown to mimic reasonably well the fluctuations in commodity markets and are thus likely to be suitable tools for strategic asset allocation.

HYBRID MOMENTUM/TERM STRUCTURE-ENHANCED INDICES

Methodology

A strategy that jointly exploits momentum and TS signals is put forward in Fuertes, Miffre & Rallis (2010) in a long-short framework. Here we deploy a similar "hybrid" strategy in a long-only framework as a novel type of index-enhancement. If a specific constituent presents higher roll-returns (term structure) and better past performance (momentum) than its peers, it is expected to perform well in the near future, so its weight is adjusted upwards. On the contrary, if a constituent presents lower roll-returns and worse past performance than its peers, it is expected to perform poorly in the near future, so its weight is adjusted downwards. Accordingly, the long-only portfolio that adjusts upwards (downwards) the weights of high-roll (low-roll) commodities with good (poor) past performance is held for one month. At the end of the month, the weights are reset to a value that is derived from the original weights, past performance and the then-prevailing roll-returns as formally explained next.

In the weighting scheme based, first, on momentum and, second, on TS signals (hereafter, Momentum/TS), we begin by sorting the constituents according to the previous month's mean return and compute its median. Commodities are thus allocated into two groups, above and below the median, and the weights of the winners (losers) are adjusted upwards (downwards). This weighting scheme relies not only on past relative performance, as in formulae (2) and (3), but it also takes into account the relative roll-returns of the commodities within each group. For example, if the S&P-GSCI allocates *x*% to corn and corn pertains to the winner portfolio, our enhanced strategy will allocate more than *x*% to corn with the exact weighting determined by the relative roll-return position amongst winners. On the contrary, if the S&P-GSCI allocates *y*% to wheat and wheat belongs to the loser portfolio, our enhanced strategy will allocate less than *y*% to wheat with the exact weighting determined by the relative roll-return position amongst losers.

Since there is no reason for sorting on first, past performance and second, roll-returns, we also implement the reverse hybrid TS/Momentum strategy. Accordingly, we first sort the index constituents according to roll-return and calculate its median. The cross-section is then divided into two groups, below-or-equal and above this median; inside each group, the original weights of the commodities are adjusted according to the previous month's relative mean returns.

Performance and Risk Profile of Hybrid Indices

Summary statistics for the two hybrid-enhancement strategies are given in Table V, columns 5-6. The outperformance relative to the original indices (*i.e.* spreads) amounts to 2.12% a year on average. The Sharpe ratios of the enhanced indices at 0.2789 on average are nearly twice those of the traditional indices at 0.1543. Similarly, the annualized alphas of the enhanced indices at 2.13% on average are positive both statistically and economically, and the performance of the hybrid indices does not merely reflect a premium for taking liquidity risk ($\beta_{Liquidity} = 0$).

Regarding the risk profile of the hybrid enhanced-indices, their tracking errors are small at 3.67% on average. Moreover, the absolute departure from unity of their index betas averages out at 0.0286 and the correlations between their returns and those of first-generation indices stay high, ranging from 97.12% to 98.49%. To complete the picture, the 99% VaR of the TS/Momentum index at 0.2078 (S&P-GSCI) and 0.1435 (DJ-UBSCI) is virtually identical to that of first-generation indices at, respectively, 0.2109 and 0.1406. The upshot is that the hybrid (momentum *and* term structure) index enhancement results in commodity portfolios which offer investors not only outperformance relative to the original indices but a similar risk profile too.

A comparison across index-enhancement strategies reveals that the risk-adjusted performance of momentum- and/or TS-enhanced indices (Table V) appears inferior to that of maturity-enhanced indices (Tables II and IV). Thus contract maturity stands out as a better signal for tactical asset allocation than past performance or roll-returns. To illustrate, the Sharpe ratios reported for maturity-enhanced indices are in the ballpark figure of 0.50, essentially doubling those for momentum or/and TS-enhanced indices. Similarly, the maturity-enhanced indices earn higher annualized alphas of 4.43% on average versus 1.97% for the momentum- or/and TS-enhancement. In the same vein, the mean spreads are higher for the maturity-enhanced indices.

A final noteworthy aspect of momentum- and/or TS-enhanced indices is that the constituents' weights are, by construction, more variable over time than those of first-generation indices. This is illustrated in Appendix C for the S&P-GSCI. As measured by the standard deviation of each weight time-series, the increase in weighting volatility of the enhanced indices amounts numerically to a 1.26:1 ratio for the combined Momentum/TS signal, 1.25:1 for the individual momentum signal and 1.27:1 for the individual term structure signal. Although the volatility increase is not dramatic, it nevertheless serves as warning that part of the outperformance may be a compensation for an increase in transaction costs.[16] We are reasonably confident, however, that the additional trades required for mimicking the momentum and/or TS-enhanced indices will not

[16] Our monthly *frequency* of weight re-allocation for the momentum- and/or TS-enhanced indices replicates the typical monthly roll schedules of the original index providers (see Table 1). However, it should be noted also that for some contracts in the original indices the roll schedule is less frequent than monthly whereas we are enforcing a monthly rolling schedule throughout. As a result, the number of trades and thus the transaction costs incurred are likely to be somewhat higher for the enhanced indices.

wipe out their incremental mean returns and alphas for various reasons. The cost of commodity futures trading is negligible (less than 0.033%) as highlighted in Fuertes, Miffre & Rallis (2010), the cross-section on which the strategies are implemented is small (up to 30 commodities) and the assets traded are located in the front-end of the curve, thus very liquid. All these aspects lend support to our contention that alphas should not vanish net of trading costs.[17]

COMPARISON WITH PREVIOUS RESEARCH

Several methodological differences can be identified between our paper and existing commodity markets research (*e.g.* Miffre & Rallis, 2007; Shen, Szakmary & Sharma, 2007; Fuertes, Miffre & Rallis, 2010; Mouakhar & Roberge, 2010; Szakmary, Shen & Sharma, 2010). First, the only existing study on maturity signals is by Mouakhar & Roberge (2010) but their main focus is roll-yield optimization, only 10 commodities are considered, and liquidity risk is not accounted for. Second, the profitability of momentum and/or TS-based strategies is analyzed here from the viewpoint of long-only passive commodity investors, while former papers that exploit such signals opt for a long-short active framework. In this respect, the passive momentum and/or TS index-enhancement methodology and analysis carried out here is novel. Third, the present weighting scheme is based on the original weights of index providers which are adjusted upwards or downwards based on past performance and/or roll-returns, as formalized in formulae (2) and (3), while existing long-short papers opt simply for equal weights across portfolio constituents.

[17] The difference between gross and net mean returns in Fuertes, Miffre & Rallis (2010) equals 0.65% across the momentum and/or TS portfolios with ranking and holding periods of 1 month. In their analysis, the cost of tracking the adopted benchmark is 0.21% a year. Thus the average incremental cost of tracking the enhanced indices as opposed to the mainstream benchmark can be approximated by the difference between these two costs at 0.44%. If this transaction cost estimate is applied in the present context, the average annual alphas net of transaction costs are still economically significant at 0.91% for the momentum-enhanced indices, 1.84% for the TS-enhanced indices and 1.69% for the hybrid indices.

Fourth, all index constituents of the traditional indices are included in our momentum and/or TS-enhanced portfolios whereas previous studies typically pick extreme performers out of the available cross-section. Last but not least, no other study has run a contest between all three signals (momentum, term structure and maturity), either in active or passive settings.

Notwithstanding the above sample and methodological differences, it is important to place our findings in the context of those previously reported. The average Sharpe ratios of long-short commodity portfolios range from 0.4051 (Miffre & Rallis, 2007) to 0.8958 (Fuertes, Miffre & Rallis, 2010) while those reported in Erb & Harvey (2006), Gorton & Rouwenhorst (2006), Shen, Szakmary & Sharma (2007), and Szakmary, Shen & Sharma (2010) fall in between. These measures beat the Sharpe ratios of our long-only enhanced indices ranging from 0.2205 to 0.5753 (as reported in Tables II and V) which reinforces the consensus view that institutional investors constrained by long-only mandates are relatively worse off. The superior risk-return profile of long-short strategies vis-à-vis the constrained long-only ones hinges on the fact that the former enable investors to capitalize on both the positive returns of backwardated commodities and the negative returns of contangoed commodities.

Our analysis establishes that the traditional index average returns of 3.68% (S&P-GSCI) and 1.97% (DJ-UBSCI) per annum can be increased to 8.73% and 5.85%, respectively, by departing from the conventional rolling methodology through simple maturity-enhanced strategies. On average across the two indices the improvement afforded is 4.47% across the 3, 6, 9 and 12-month maturity contracts. This improvement is comparable to that of 4.80% reported in Mouakhar & Roberge (2010) despite the fact that our long-only maturity enhancement strategy does not rely on roll-return optimization like theirs.

RISK DIVERSIFICATION AND INFLATION HEDGING

The empirical analysis thus far has documented that the enhanced indices have betas close to unity and very high correlations with traditional indices. Hence, a tentative conclusion is that the enhanced mimicking portfolios are as useful as first-generation indices for strategic asset allocation (*i.e.* risk diversification and inflation hedging). In order to strengthen this conclusion, we compute the pairwise correlations between the monthly returns of each commodity portfolio and those of two *fixed income* indices (J.P.Morgan U.S. Government Bond Index and J.P.Morgan U.S. 3 Month Cash Index) and two *equity* indices (S&P 500 and Russell 2000). The former three indices are chosen on the basis that they are part of the standard asset allocation of U.S. investors. Russell 2000 is added because it has become the standard benchmark for "small-cap" mutual funds. Table VI sets out the results.

[Table VI around here]

Our findings square well with the extant literature (*e.g.* Erb & Harvey, 2006) in suggesting that the traditional indices are weakly correlated with fixed income indices (at -5.38% on average) and equity indices (at 15.14% on average). A piece of evidence not documented as yet in any other study is that the pairwise correlations between each of the enhanced indices and the fixed income/equity indices are virtually undistinguishable from the aforementioned correlations. We test the null hypothesis that the correlation between a first-generation index and a fixed income/equity index is identical to that between an enhanced index and the same fixed income/equity index. Unreported *t*-statistics for the differential correlation are all very small ranging from -0.915 to 0.499. It can thus be inferred that the co-movement of the S&P-GSCI/ DJ-UBSCI and traditional asset classes is broadly similar to that of the enhanced indices and traditional asset classes.[18] In sum, our results suggest that the outperformance of the enhanced indices does not come at the expense of inferior risk diversification.

Another crucial strategic role that traditional commodity indices have been shown to play is inflation hedging (see *e.g.* Bodie, 1983). To consider this aspect, we measure quarterly[19] correlations between commodity index returns and unexpected CPI inflation defined as the difference between actual (or realized) inflation and expected inflation. The latter is estimated in two ways. First, an ARMA(1,1) model is fitted to quarterly inflation and its one-quarter-ahead projection (using information up to quarter *t*-1) is adopted as proxy for expected inflation at *t*. Second, assuming random walk behavior for inflation and accounting for seasonality, as in Erb & Harvey (2006), the expectation for inflation at quarter *t* is the inflation level at *t*-4, *i.e.* the same quarter of the previous year. The last column of Table VI sets out the results. A high positive correlation is indicative of an effective inflation hedge. However, it should be borne in mind that commodities have less than half weight in the CPI (about 40%; the rest corresponds to services) which limits the ability of any commodity index to act as a "perfect" hedge.

The correlations between unexpected inflation and traditional commodity indices are significantly positive and relatively high, *e.g.* at 0.50 (S&P-GSCI) and 0.46 (DJ-UBSCI) according to the ARMA approach.[20] The correlations between unexpected inflation and the

[18] Monthly data on U.S. fixed income and equity indices are obtained from *Datastream*. We also considered less standard asset classes that include foreign investment using data on J.P.Morgan Global (fixed income) indices pertaining to Europe, Asia and Africa and on MSCI (equity) indices for Europe, Asia-Pacific and Latin America. The unreported pairwise correlations of the commodity index returns with these indices, available from the authors upon request, lead to the same conclusions.

[19] For the purpose of demonstrating the inflation hedging effectiveness of commodities, previous studies have noted the larger signal/noise ratio inherent in lower frequencies. For instance, Bodie & Rosansky (1980) and Gorton & Rouwenhorst (2006) use quarterly data whereas Erb & Harvey (2006) opt for annual observations. We report results based on quarterly data but as a robustness check we repeat the analysis at monthly frequency. Although the correlations are smaller, on the whole the same pattern as with quarterly frequency was revealed. The U.S. CPI observations are obtained from *Datastream*.

[20] There is consensus that inflation is a persistent process but the evidence on whether it contains a unit root (in line with the random walk assumption) is not clearcut. An augmented Dickey-Fuller (ADF) type

enhanced indices are equally high at 0.53 (S&P-GSCI) and 0.49 (DJ-UBSCI) on average using the same ARMA modeling approach. This analysis shows that the enhanced indices are as good a hedge against inflation shocks as the first-generation indices.

CONCLUSIONS

Until relatively recently, investors interested in passively holding commodities as part of their strategic asset allocation resorted to first-generation indices such as the S&P-GSCI or the DJ-UBSCI. However, various aspects of these indices render them sub-optimal; amongst them, their low rebalancing frequency, the fact that they only trade front-end contracts and ignore signals known to be important drivers of commodity futures prices such as past performance and roll-return. Since the inception of the Deutsche Bank Liquid Commodity Index in 2003, a plethora of second-generation indices has been "sold" to long-only investors as providing both broad exposure to commodity markets and enhanced performance. As a result of this index proliferation, it has become increasingly bewildering for investors to choose among competing indices. This article extends past research by offering a formal comparison of two first-generation indices, S&P-GSCI and DJ-UBSCI, and various enhanced versions thereof that exploit signals related to the time-to-maturity of the contracts, momentum and the term structure.

We draw three main conclusions from our analysis. First, the enhanced indices offer positive alpha of 3.20% per annum on average vis-à-vis traditional indices and therefore can be utilized for tactical asset allocation. Second, the largest enhancement is extracted from maturity signals by

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test for inflation over the 1989Q1-2008Q4 period cannot reject the unit root null hypothesis (ADF statistic = -2.49; *p*-value = 0.121) but the same test applied to monthly inflation over the same period strongly rejects it (ADF statistic = -8.23). Moreover, although in theory unexpected inflation should be serially independent, only the ARMA approach delivers an unexpected inflation series that closely resembles white noise as suggested by the Ljung-Box Q_4 test (statistic = 5.1281; *p*-value = 0.274). This evidence favors the ARMA approach to model unexpected inflation.

targeting the distant contracts of up to 12 months. This yields a strong alpha of up to 5.49% per annum that is not merely a compensation for liquidity risk. Third, the enhanced indices are as appropriate for strategic asset allocation (*i.e.* risk diversification and inflation hedging), as the traditional S&P-GSCI and DJ-UBSCI. The overall conclusion is that second-generation indices are more efficient than traditional ones.

A possible extension of this study includes the design of long-only maturity-enhanced indices that assign higher weights to commodities with high past performance and above-average roll-returns and lower weights to commodities with low past performance and below-average roll-returns. Given that momentum, term structure and maturity signals are profitable in isolation, it is possible that a combination of them will add further value for investors.

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Table I. Commodities and Active Contracts in the S&P-GSCI and DJ-UBSCI

Commodity	Ticker	Exchange	Start Date	S&P-GSCI	DJ-UBSCI
Aluminum	LA	LME	Jan-89	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Brent Crude	CO	ICE	Jul-91	H J K M N Q U V X Z F G	
Cocoa	CC	NYBOT	Jan-89	H H K K N N U U Z Z Z H	H H K K N N U U Z Z Z H
Coffee	KC	NYBOT	Jan-89	H H K K N N U U Z Z Z H	H H K K N N U U Z Z Z H
Copper	LP	LME	Jan-89	G H J K M N Q U V X Z F	
Copper NYMEX	HG	CMX-NYMEX	Aug-90		H H K K N N U U Z Z Z H
Corn	C	CBT	Dec-88	H H K K N N U U Z Z Z H	H H K K N N U U Z Z Z H
Cotton #2	CT	NYBOT	Jan-89	H H K K N N Z Z Z Z Z H	H H K K N N Z Z Z Z Z H
Crude Oil	CL	NYMEX	Nov-88	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Feeder Cattle	FC	CME	Nov-88	H H J K Q Q Q U V X F F	
Gas Oil	QS	ICE	Jul-89	G H J K M N Q U V X Z F	
Gasoline	HU	NYMEX	Dec-88	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Gasoline RBOB	XB	NYMEX	Oct-05	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Gold	GC	CMX-NYMEX	Dec-88	G J J M M Q Q Z Z Z Z G	G J J M M Q Q Z Z Z Z G
Heating Oil #2	HO	NYMEX	Dec-88	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Lead	LL	LME	Jan-89	G H J K M N Q U V X Z F	
Lean Hogs	LH	CME	Dec-88	G J J M M N Q V V Z Z G	G J J M M N Q V V Z Z G
Live Cattle	LC	CME	Dec-88	G J J M M Q Q V V Z Z G	G J J M M Q Q V V Z Z G
Natural Gas	NG	NYMEX	Jul-90	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Nickel	LN	LME	Jan-89	G H J K M N Q U V X Z F	H H K K N N U U X X F F
Orange Juice	JO	NYMEX	Nov-88	H H K K N N U U X X F F	
Platinum	PL	NYMEX	Nov-88	J J J N N N V V V F F F	
Silver	SI	CMX-NYMEX	Dec-88	H H K K N N U U Z Z Z H	H H K K N N U U Z Z Z H
Soybean Oil	BO	CBT	Oct-88		H H K K N N Z Z Z Z F F
Soybeans	S	CBT	Nov-88	H H K K N N X X X X F F	H H K K N N X X X X F F
Sugar #11	SB	NYBOT	Jan-89	H H K K N N V V VH H H	H H K K N N V V VH H H
Tin	LT	LME	Aug-89	G H J K M N Q U V X Z F	
Wheat (Chicago)	W	CBT	Jan-89	H H K K N N U U Z Z Z H	H H K K N N U U Z Z Z H
Wheat (Kansas)	KW	KCBOT	Dec-88	H H K K N N U U Z Z Z H	
Zinc	LX	LME	Jul-91	G H J K M N Q U V X Z F	H H K K N N U U X X F F

Notes. The table contains the futures months included in the S&P-GSCI and DJ-UBSCI at the beginning of each calendar month, starting with January. The letter codes are F (January), G (February), H (March), J (April), K (May), M (June), N (July), Q (August), U (September), V (October), X (November) and Z (December).

Table II. Performance, Risk and Liquidity of Maturity-Enhanced Indices

	S&P-GSCI					DJ-UBSCI				
	Index	3-month	6-month	9-month	12-month	Index	3-month	6-month	9-month	12-month
Panel A: Summary statistics for the first generation and maturity-enhanced indices										
Annualized arithmetic mean	0.0368	0.0866	0.0875	0.0869	0.0883	0.0197	0.0497	0.0595	0.0618	0.0629
Annualized geometric mean	0.0148	0.0668	0.0719	0.0733	0.0754	0.0096	0.0396	0.0510	0.0541	0.0557
Annualized volatility	0.2126	0.1911	0.1691	0.1578	0.1535	0.1451	0.1381	0.1265	0.1202	0.1157
Sharpe ratio	0.1730	0.4531	0.5172	0.5508	0.5753	0.1356	0.3595	0.4707	0.5142	0.5438
Skewness	-0.2637	-0.4380	-0.6200	-0.7105	-0.7287	-0.6811	-0.7728	-0.8632	-0.8485	-0.8888
Kurtosis	5.4148	6.5498	7.6158	8.1703	8.3765	6.1399	6.7854	7.9853	8.7129	9.0936
99% VaR (Cornish-Fisher)	0.2109	0.1911	0.1688	0.1563	0.1519	0.1406	0.1319	0.1211	0.1169	0.1120
Correlation with index		0.9779	0.9436	0.9208	0.9130		0.9898	0.9603	0.9381	0.9297
Tracking error relative to index		0.0401	0.0561	0.0617	0.0627		0.0197	0.0354	0.0417	0.0427
Annualized alpha		**0.0515**	**0.0574**	**0.0595**	**0.0618**		**0.0299**	**0.0418**	**0.0453**	**0.0472**
		(5.59)	(4.45)	(4.19)	(3.35)		(4.84)	(3.62)	(3.38)	(3.38)
Beta relative to index		**0.8791**	**0.7504**	**0.6836**	**0.6592**		**0.9422**	**0.8372**	**0.7770**	**0.7414**
		(-4.71)	(-6.13)	(-6.87)	(-7.25)		(-3.72)	(-4.63)	(-5.20)	(-5.82)
Panel B: Summary statistics for the spreads										
Annualized arithmetic mean		**0.0467**	**0.0476**	**0.0470**	**0.0484**		**0.0287**	**0.0384**	**0.0406**	**0.0417**
		(4.30)	(2.69)	(2.25)	(2.21)		(5.62)	(3.76)	(3.20)	(3.05)
Correlation with index		-0.5406	-0.6880	-0.7377	-0.7566		-0.3932	-0.5561	-0.6138	-0.6608

Notes. The statistics for S&P-GSCI (DJ-UBSCI) are based on the period October 1988 (January 1991) to November 2008. Spread refers to the average of the returns differential between the maturity-enhanced and first-generation indices. *t*-statistics in parentheses are for the null hypothesis that alpha is 0, beta relative to index is 1 and the arithmetic mean of the spread is 0. Bold denotes rejection at the 1%, 5% or 10% level.

Table III. Average Open Interests of Index Constituents

	Contract maturity				
	Front	3-month	6-month	9-month	12-month
Aluminum	406	417	197	131	89
Brent Crude	89,428	42,687	17,746	10,889	7,527
Cocoa	18,860	13,690	5,923	2,720	2,720
Coffee	20,862	8,153	1,092	576	552
Copper	3,928	16,348	2,893	1,428	806
Corn	130,397	84,111	15,727	6,015	4,385
Cotton #2	17,564	15,936	1,949	498	488
Crude Oil	68,712	30,129	18,403	12,779	9,388
Feeder Cattle	5,913	2,834	363	363	363
Gas Oil	30,412	18,693	7,449	4,353	2,814
Gasoline	27,009	10,539	2,706	1,302	1,274
Gasoline RBOB	51,913	14,193	4,636	1,925	1,185
Gold	52,733	23,826	7,359	3,264	2,081
Heating Oil #2	48,372	15,599	7,389	3,531	1,479
Lean Hogs	16,648	11,046	2,020	379	379
Live Cattle	38,107	20,406	1,994	1,722	1,043
Natural Gas	53,567	24,804	16,851	12,274	8,792
Orange Juice	7,423	3,179	399	98	97
Platinum	7,885	1,962	1,939	1,939	1,939
Silver	36,000	9,311	2,700	805	677
Soybean Oil	23,273	22,761	6,997	1,695	1,011
Soybeans	46,735	31,046	8,583	2,557	2,677
Sugar #11	108,660	33,192	7,129	6,597	6,597
Wheat (Chicago)	45,702	20,977	4,208	2,911	2,776
Wheat (Kansas)	21,607	6,201	3,506	3,510	3,509
Average	38,885	19,282	6,006	3,370	2,586

Notes. The table reports open interests averaged over the period January 1991 to November 2008.

Table IV. Liquidity-Adjusted Performance of Maturity-Enhanced Indices

	S&P-GSCI				DJ-UBSCI			
	3-month	6-month	9-month	12-month	3-month	6-month	9-month	12-month
α	**0.0471**	**0.0514**	**0.0528**	**0.0549**	**0.0277**	**0.0379**	**0.0405**	**0.0422**
	(5.46)	(4.26)	(3.99)	(4.08)	(6.15)	(4.67)	(4.25)	(4.32)
β_{Index}	**0.8879**	**0.7630**	**0.6978**	**0.6736**	**0.9451**	**0.8423**	**0.7834**	**0.7480**
	(74.95)	(46.13)	(38.47)	(36.50)	(105.53)	(52.10)	(41.33)	(38.53)
$\beta_{Liquidity}$	**0.1162**	**0.1663**	**0.1876**	**0.1907**	**0.0513**	**0.0882**	**0.1109**	**0.1138**
	(4.75)	(4.87)	(5.01)	(5.00)	(4.20)	(4.00)	(4.29)	(4.30)
R^2	96.00%	90.04%	86.25%	84.96%	98.13%	92.76%	88.97%	87.52%

Notes. The table presents regression coefficients from a two-factor model that treats as risk factors the underlying first-generation index alongside a commodity-based liquidity risk premium à la Pastor and Stambaugh (2003). The regression sample starts in January 1989 (January 1991) for the S&P-GSCI (DJ-UBSCI) and ends on November 2008 for both. *t*-statistics in parentheses are for the null hypothesis that the coefficient is zero. Bold indicates significant at the 10%, 5% or 1% levels. The alpha (α) measure has been annualized.

Table V. Performance, Risk and Liquidity of Momentum or/and Term Structure-Enhanced Indices

	Index		Momentum		Term Structure (TS)		Momentum / TS		TS / Momentum	
	S&P-GSCI	DJ-UBSCI	S&P-GSCI	DJ-UBSCI	S&P-GSCI	DJ-UBSCI	S&P-GSCI	DJ-UBSCI	S&P-GSCI	DJ-UBSCI
Panel A: Summary statistics for the first and second generation indices										
Annualized arithmetic mean	0.0368	0.0197	0.0499	0.0343	0.0636	0.0407	0.0526	0.0367	0.0675	0.0450
Annualized geometric mean	0.0148	0.0096	0.0283	0.0229	0.0414	0.0290	0.0310	0.0252	0.0454	0.0335
Annualized mean spread			0.0129	0.0146	**0.0245**	**0.0199**	**0.0150**	**0.0168**	**0.0288**	**0.0242**
			(1.52)	(1.54)	(2.62)	(2.29)	(1.81)	(1.90)	(3.22)	(2.87)
Annualized volatility	0.2126	0.1451	0.2110	0.1554	0.2047	0.1503	0.2087	0.1546	0.2068	0.1503
Sharpe ratio	0.1730	0.1356	0.2363	0.2205	0.3105	0.2707	0.2521	0.2372	0.3266	0.2997
Skewness	-0.2637	-0.6811	-0.1036	-0.5180	-0.2240	-0.6276	-0.1218	-0.5494	-0.1381	-0.5874
Kurtosis	5.4148	6.1399	5.6806	5.5570	5.8541	6.2428	5.6722	5.6958	5.6177	5.7296
99% VaR (Cornish-Fisher)	0.2109	0.1406	0.2150	0.1497	0.2065	0.1458	0.2119	0.1489	0.2078	0.1435
Correlation with index			0.9843	0.9673	0.9811	0.9701	0.9849	0.9712	0.9827	0.9721
Tracking error relative to index			0.0373	0.0395	0.0397	0.0366	0.0362	0.0369	0.0384	0.0354
Panel B: Regression coefficients from the liquidity-enhanced index model										
α			0.0134	0.0135	**0.0258**	**0.0198**	**0.0159**	**0.0158**	**0.0295**	**0.0241**
			(1.59)	(1.44)	(2.89)	(2.28)	(1.95)	(1.80)	(3.34)	(2.86)
β_{Index}			**0.9780**	**1.0359**	**0.9458**	**1.0054**	**0.9675**	**1.0348**	**0.9589**	**1.0061**
			(84.84)	(55.41)	(77.18)	(57.98)	(86.48)	(59.23)	(71.58)	(60.09)
$\beta_{Liquidity}$			0.0109	0.0056	0.0171	-0.0066	0.0082	0.0044	0.0139	-0.0087
			(0.46)	(0.22)	(0.68)	(-0.28)	(0.36)	(0.18)	(0.54)	(-0.38)
R^2			96.90%	93.57%	96.27%	94.11%	97.01%	94.33%	95.93%	94.49%

Notes. The results for S&P-GSCI (DJ-UBSCI) are based on the period Oct, 1988 (Jan, 1991) to Nov, 2008. Spread refers to the average of the return differential between the second- and first-generation indices. t-statistics in parentheses in Panel A are for the null that the arithmetic mean of the annualized spread is 0. The t-statistics in parentheses in Panel B are for the null that the coefficients of the two-factor model are 0. The alpha (α) measure has been annualized. Bold denotes rejection at the 1%, 5% or 10% level.

Table VI. Correlation of Commodities with Bonds, Equities and Unexpected Inflation.

	Fixed Income Indices		Equity Indices		Unexpected Inflation	
	US Govt	US 3m Cash	S&P500	Russell 2000	ARMA	EH06
Panel A: S&P-GSCI						
Index	-0.0457	-0.0397	0.0546	0.1229	0.5042	0.4247
	(-0.704)	(-0.611)	(0.843)	(1.906)	(5.157)	(4.143)
3-month	-0.0865	-0.0767	0.0695	0.1316	0.5240	0.4421
	(-1.337)	(-1.185)	(1.072)	(2.043)	(5.434)	(4.353)
6-month	-0.1176	-0.1077	0.0891	0.1410	0.5592	0.4492
	(-1.823)	(-1.668)	(1.377)	(2.913)	(5.957)	(4.441)
9-month	-0.1287	-0.1186	0.0958	0.1404	0.5820	0.4529
	(-1.9981)	(-1.838)	(1.482)	(2.184)	(6.321)	(4.486)
12-month	-0.1293	-0.1189	0.1003	0.1429	0.5869	0.4564
	(-2.008)	(-1.843)	(1.552)	(2.222)	(6.401)	(4.530)
Momentum	-0.0491	-0.0473	0.0429	0.1145	0.4912	0.4042
	(-0.756)	(-0.729)	(0.661)	(1.774)	(4.980)	(3.902)
TS	-0.0722	-0.0594	0.0524	0.1262	0.5117	0.4242
	(-1.114)	(-0.915)	(0.809)	(1.958)	(5.259)	(4.138)
Momentum/TS	-0.0559	-0.0467	0.0406	0.1127	0.5017	0.4202
	(-0.862)	(-0.719)	(0.625)	(1.747)	(5.122)	(4.090)
TS/Momentum	-0.0632	-0.0539	0.0103	0.1197	0.4987	0.4119
	(-0.974)	(-0.831)	(0.692)	(1.857)	(5.082)	(3.992)
Panel B: DJ-UBSCI						
Index	-0.0377	-0.0921	0.1895	0.2337	0.4626	0.3412
	(-0.551)	(-1.349)	(2.817)	(3.507)	(4.365)	(3.036)
3-month	-0.0673	-0.1143	0.1990	0.2343	0.4770	0.3550
	(-0.984)	(-1.679)	(2.964)	(3.517)	(4.541)	(3.177)
6-month	-0.0911	-0.1428	0.2108	0.2327	0.5097	0.3672
	(-1.336)	(-2.106)	(3.147)	(3.492)	(4.956)	(3.303)
9-month	-0.0981	-0.1493	0.2086	0.2262	0.5456	0.3789
	(-1.438)	(-2.203)	(3.112)	(3.389)	(5.447)	(3.426)
12-month	-0.0983	-0.1504	0.2100	0.2284	0.5577	0.3918
	(-1.441)	(-2.219)	(3.135)	(3.423)	(5.622)	(3.563)
Momentum	-0.0356	-0.0895	0.1528	0.2125	0.4472	0.3062
	(-0.520)	(-1.311)	(2.257)	(3.174)	(4.183)	(2.691)
TS	-0.0610	-0.0962	0.1707	0.2315	0.4869	0.3443
	(-0.893)	(-1.409)	(2.528)	(3.474)	(4.664)	(3.068)
Momentum/TS	-0.0435	-0.0864	0.1520	0.2163	0.4668	0.3204
	(-0.635)	(-1.265)	(2.244)	(3.233)	(4.417)	(2.830)
TS/Momentum	-0.0481	-0.0883	0.1639	0.2248	0.4683	0.3331
	(-0.703)	(-1.293)	(2.424)	(3.367)	(4.434)	(2.956)

Notes. Columns two to five report Pearson correlations between monthly returns of commodity portfolios, and two traditional asset classes, fixed income and equity. The last two columns report correlations between quarterly returns and quarterly unexpected inflation; the latter is proxied by the residuals of an ARMA model fitted to CPI inflation and by the year-on-year CPI inflation change as in Erb & Harvey (2006). *t*-statistics in parenthesis are for the significance of the correlation.

APPENDIX A

Baseline Replication of Commodity Indices

	S&P-GSCI		DJ-UBSCI	
	Index	Baseline replication	Index	Baseline replication
Annualized arithmetic mean	0.0368	0.0382	0.0197	0.0207
Annualized geometric mean	0.0148	0.0148	0.0096	0.0106
Annualized volatility	0.2126	0.2125	0.1451	0.1452
Reward/risk ratio	0.1730	0.1799	0.1356	0.1426
Skewness	-0.2637	-0.2513	-0.6811	-0.6624
Kurtosis	5.4148	5.4322	6.1399	6.0249
99% VaR (Cornish-Fisher)	0.2109	0.2111	0.1406	0.1404
Correlation with index		0.9992		0.9998
Tracking error relative to index		0.0083		0.0026
Annualized alpha relative to index		0.0022		0.0010
		(1.20)		(1.62)
Beta relative to index		0.9987		1.0003
		(-0.51)		(0.27)

Notes. The *t*-statistics in parentheses are for the null hypothesis that alpha is 0 and beta is 1.

APPENDIX B

Modeling the Liquidity Risk Premium of Commodity Futures

We follow the three-step procedure of Pastor & Stambaugh (2003) to derive a Liquidity Risk Premium (LRP) factor in the context of commodity futures.[21] In step one, a measure of liquidity is obtained for each commodity futures contract in a given month t using daily data within the month; this liquidity measure is the OLS estimate of $\gamma_{i,t}$ in the regression

$$r^{e}_{i,t,d+1} = \theta_{i,t} + \phi_{i,t} r_{i,t,d} + \gamma_{i,t} \mathrm{sign}\left(r^{e}_{i,t,d}\right) \cdot OI_{i,t,d} + \epsilon_{i,t,d+1} \tag{B1}$$

where $r_{i,t,d}$ is the return of the front-end commodity contract i on day $d(= 1, \dots, D)$ of month t; $r^{e}_{i,t,d+1}$ (the superscript "e" denotes excess) is defined as the differential $r_{i,t,d} - r_{m,t,d}$ with $r_{m,t,d}$ the return of an equally-weighted monthly-rebalanced portfolio of all commodities (used as a proxy for the commodity market portfolio) on day d of month t; $OI_{i,t,d}$ is the open interest of contract i on day d of month t times the \$ value of the contract on day d of month t. The idea is that contracts with low liquidity should have largely negative $\gamma_{i,t}$. A monthly liquidity measure for commodity futures markets is obtained by combining the liquidity measures of individual futures, $\hat{\gamma}_t = \left(\frac{1}{N}\right) \sum_{i=1}^{N} \hat{\gamma}_{i,t}$, for each month t from December 1983 to November 2008.

In step two, the innovation in liquidity, $\mathcal{L}_t$, is obtained via the following regression

$$\Delta\tilde{\gamma}_t = a + b\Delta\tilde{\gamma}_{t-1} + c\left(\frac{m_{t-1}}{m_1}\right)\hat{\gamma}_{t-1} + u_t \tag{B2}$$

as the estimated error or residual $\mathcal{L}_t \equiv \hat{u}_t$; in this regression equation, $\Delta\tilde{\gamma}_t$ denotes the monthly change in $\hat{\gamma}_t$ adjusted for inflation in the cost of trade, $\Delta\tilde{\gamma}_t = \left(\frac{m_t}{m_1}\right)\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(\hat{\gamma}_{i,t} - \hat{\gamma}_{i,t-1}\right)$, where

[21] The commodities included in this analysis are as follows: Brent crude oil, cocoa, coffee, copper, corn, cotton, electricity, ethanol, feeder cattle, gasoil, gold, heating oil, lean hogs, light crude oil, live cattle, lumber, natural gas, orange juice, palladium, platinum, propane, rice, silver, soybean meal, soybean oil, soybeans, sugar, unleaded gasoline, western plywood and wheat.

m_t is the total market capitalization of commodities in month t measured as the sum across contracts of the OI of each contract times its $ value in month t.

At a final step, we obtain the LRP of commodity futures by, first, running regressions of the returns of the front commodity contract on a constant, the liquidity shocks $\mathcal{L}_t$ and the market returns using the first five years of monthly data,

$$r_{i,t} = \beta_i^0 + \beta_i^{\mathcal{L}} \mathcal{L}_t + \beta_i^M r_{m,t} + \epsilon_{i,t} \tag{B3}$$

and second, by sorting the commodities into deciles based on their estimated historical betas, $\hat{\beta}_i^{\mathcal{L}}$, from the most liquid (low $\hat{\beta}_{\mathrm{i}}^{\mathcal{L}}$) to the least liquid (high $\hat{\beta}_i^{\mathcal{L}}$). We then create 5 equally-weighted portfolios, buy the 5th quintile (less liquid commodities), sell the 1st quintile (most liquid commodities) and hold the resulting portfolio over the following 12 months. At the end of the 12-month period, the same procedure is repeated by rolling the estimation window 12-months forward and re-estimating equation (B3) to generate the returns of another portfolio. Thus each long-short portfolio is formed at year end (i.e. December of year *t*-1) using information of the previous 5 years and is held for 12 months (from January to December of year *t*).

So as to avoid leverage, the liquidity risk premium is assumed to be fully-collateralized, meaning that the return of the long-short portfolio is defined as half the return of the long portfolio minus half the return of the short portfolio. The long-short portfolio return thus obtained represents a LRP proxy in commodity futures markets.

APPENDIX C

Summary Statistics of Constituents Weights for First-Generation and Enhanced S&P-GSCI

	First-generation		Momentum		Term structure (TS)		TS/Momentum	
	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
Aluminum	0.0217	0.0163	0.0207	0.0212	0.0210	0.0200	0.0193	0.0223
Brent Crude	0.0459	0.0616	0.0446	0.0612	0.0471	0.0637	0.0462	0.0629
Cocoa	0.0031	0.0017	0.0076	0.0117	0.0042	0.0068	0.0053	0.0095
Coffee	0.0166	0.0112	0.0195	0.0200	0.0159	0.0205	0.0149	0.0182
Copper	0.0253	0.0064	0.0270	0.0170	0.0344	0.0161	0.0324	0.0168
Corn	0.0471	0.0159	0.0450	0.0253	0.0350	0.0256	0.0375	0.0243
Cotton #2	0.0261	0.0115	0.0258	0.0202	0.0220	0.0210	0.0223	0.0207
Crude Oil	0.1973	0.1119	0.1917	0.1127	0.1953	0.1133	0.1945	0.1133
Feeder Cattle	0.0018	0.0032	0.0028	0.0082	0.0046	0.0116	0.0033	0.0088
Gas Oil	0.0145	0.0199	0.0132	0.0212	0.0151	0.0227	0.0141	0.0225
Gasoline	0.0749	0.0590	0.0704	0.0604	0.0754	0.0644	0.0744	0.0616
Gasoline RBOB	0.0023	0.0085	0.0019	0.0081	0.0026	0.0106	0.0023	0.0096
Gold	0.0226	0.0056	0.0224	0.0143	0.0268	0.0111	0.0279	0.0149
Heating Oil #2	0.1217	0.0770	0.1151	0.0817	0.1121	0.0829	0.1134	0.0823
Kansas Wheat	0.0049	0.0069	0.0048	0.0107	0.0034	0.0090	0.0035	0.0091
Lead	0.0017	0.0018	0.0055	0.0115	0.0070	0.0125	0.0068	0.0124
Lean Hogs	0.0717	0.0545	0.0701	0.0574	0.0717	0.0597	0.0710	0.0577
Live Cattle	0.1118	0.0709	0.1127	0.0729	0.1117	0.0759	0.1114	0.0745
Natural Gas	0.0567	0.0570	0.0501	0.0578	0.0435	0.0521	0.0463	0.0547
Nickel	0.0041	0.0041	0.0078	0.0137	0.0100	0.0141	0.0108	0.0151
Orange Juice	0.0012	0.0026	0.0017	0.0062	0.0017	0.0064	0.0017	0.0062
Platinum	0.0024	0.0019	0.0057	0.0096	0.0103	0.0128	0.0092	0.0109
Silver	0.0032	0.0016	0.0079	0.0113	0.0078	0.0092	0.0099	0.0120
Soybeans	0.0260	0.0076	0.0267	0.0175	0.0236	0.0164	0.0236	0.0183
Sugar #11	0.0228	0.0096	0.0247	0.0193	0.0285	0.0192	0.0269	0.0181
Tin	0.0000	0.0000	0.0017	0.0058	0.0038	0.0106	0.0034	0.0084
Wheat (Chicago)	0.0680	0.0314	0.0655	0.0377	0.0592	0.0427	0.0607	0.0405
Wheat (Kansas)	0.0049	0.0069	0.0048	0.0107	0.0034	0.0090	0.0035	0.0091
Zinc	0.0049	0.0040	0.0076	0.0135	0.0061	0.0117	0.0069	0.0135
Average	0.0347	0.0231	0.0346	0.0289	0.0346	0.0294	0.0346	0.0293
Ratio	–	–	0.9999	1.2510	0.9985	1.2700	0.9986	1.2651

Notes. The table reports for each commodity the mean and standard deviation of the weighting sequence over the sample period October 24, 1998 to November 20, 2008. At the bottom of the table we report the averages and ratio of averages from the enhanced to traditional indices.