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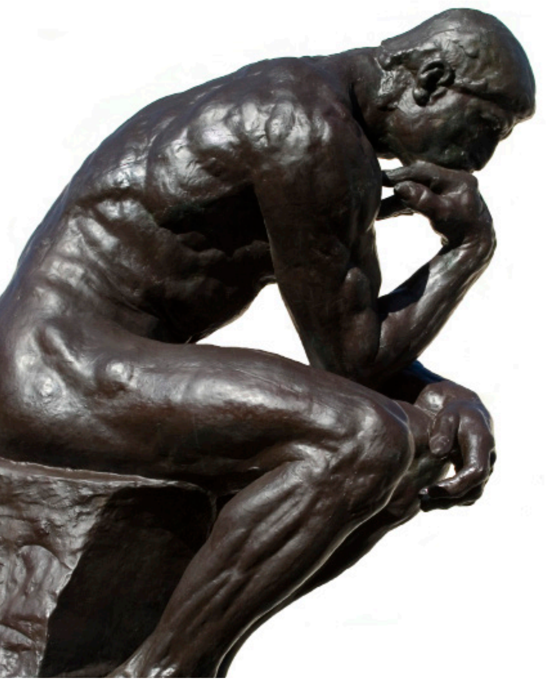

Alternative Investment Analyst Review

Comparing Three Generations of Commodity Indices: New Evidence for Portfolio Diversification

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Finding assets that reduce portfolio risk without sacrificing returns can be seen as the holy grail in portfolio diversification [Galvani and Plourde, 2009]. With one of the first studies concerning diversification benefits of commodity futures, Bodie and Rosansky [1980] demonstrate that commodities can be considered as an asset class that provides exactly this characteristic to investors. Evaluating the performance of individual commodities from 1950 to 1976, they report that adding these securities to a U.S. stock portfolio reduces overall risk without sacrificing returns. Gorton and Rouwenhorst [2006] attribute this to the fact that commodities are prone to a number of factors, such as weather, environmental developments, or unexpected supply and demand shocks which affect traditional asset classes to a lesser degree [Jensen and Mercer, 2011]. With the launch of the S&P Goldman Sachs Commodity Index (GSCI) in November 1991, investors were able to invest in a broad selection of commodity futures for the first time, without interacting in the complicated process of closing or rolling future contract positions [Georgiev, 2001]. This new possibility incited a stream of research that questions the performance of such indices in portfolios.

Satyanarayan and Varangis [1996] analyze the shift of the efficient frontier in a mean-variance framework and conclude that an investment of only 3% into the GSCI leads to a reduction in portfolio risk of over 3.6%. Georgiev [2001] reports that adding the GSCI to a global stock/bond portfolio, also including hedge funds, reduces overall risk and improves the Sharpe ratio (SR). Using a regression-based approach, evidence in favor of commodities is further reported by Belousova and Dorfleitner [2012] and Galvani and Plourde [2009]. The former study performs mean-variance (MV) spanning tests including individual futures. Focusing only on energy futures, the latter study shows that portfolio risk is reduced when commodities were held in the period from 1980 to 2008.

While in-sample properties of commodities are exhaustively studied, the literature with regard to the out-of-sample (OOS) performance is limited. The only studies considering commodities in an OOS setting are Daskalaki and Skiadopoulos [2011], You and Daigler [2012], and Bessler and Wolf [2014]. Daskalaki and Skiadopoulos [2011] show that while commodities provide gains in-sample, the reported benefits vanish out-of-sample. Using a rolling window approach and various risk coefficients, they report no diversification benefits for the GSCI and the Dow Jones-UBS Commodity Index (DJUBSCI) over the period from 1989 to 2009 and 1991 to 2009, respectively. They also challenge the diversification benefits from later generation indices. Including two second generation indices and, using significance tests in their analysis, they show that these benchmarks do not provide benefits when added to the investment universe. However, You and Daigler [2012] contradict the findings of Daskalaki and Skiadopoulos [2011]. The authors report that a MV portfolio improves when future contracts are included. Finally, Bessler and Wolf [2014] agree on the OOS risk return improvements by analyzing Sharpe ratios of different portfolio strategies and different commodity classes for a traditional U.S. investor. Using the GSCI, as well as Energy-, Metal-, Livestock- and Agriculture-futures contracts, they show that the risk-return performance improves.

Moreover, the increasing investments in the commodity markets in the early 2000s started to cast doubts on the benefits available to investors [Domanski and Heath, 2007]. Domanski and Heath [2007], Tang and Xiong [2012], and Silvennoinen and Thorp [2012] provide evidence for the financialization of this asset class. Domanski and Heath [2007], for example, argue that increased commodity investment leads to more integrated markets. Commodity markets are no longer only driven by fundamental factors, but are also prone to financial market factors. Moreover, Tang and Xiong [2012] state that rising commodity investment leads to volatility spillovers and excess correlation among commodity prices, which have a tremendous effect on investors' hedging and investment strategies. Finally, Silvennoinen and Thorp [2012] investigate the correlation of commodity and equity markets. Their results show that the increased correlation among these markets has led to weakened diversification benefits for investors. The reported evidence against the diversification benefits and the increased financialization should nevertheless be interpreted with caution. Growing research in the field of investment strategies and weighting methodologies has triggered investment companies to further improve their indices [Louie and Bourton, 2013]. Today, investors face three different generations of commodity benchmarks - furnishing them with various weighting and selection methodologies - and must address the question of whether or not diversification benefits still exist in the commodity markets [Miffre, 2012].

Since later generation indices are relatively new, research often focuses on first generation indices. Exceptions are Chong and Miffre [2010], Rallis, Miffre, and Fuertes [2012], and Miffre [2012]. Chong and Miffre [2010] consider commodity investment from a tactical asset allocation point-of-view. Comparing long-only and long-short strategies, they show that the latter outperforms the former. As a result, first generation indices that represent long-only strategies used by Daskalaki and Skiadopoulos [2011] might be considered weak diversifiers. Later generation indices, on the other hand, following different allocation strategies, also including long-short allocations, may still be beneficial. Further support for this argument is provided by Miffre and Rallis [2007] and Erb and Harvey [2006], and is validated by Fuertes, Miffre, and Rallis [2008]. Miffre and Rallis [2007] use momentum strategies, while Erb and Harvey [2006] use the futures term structure to improve roll returns. Miffre [2012] provides a classification into different generations for several indices. In total, she evaluates 38 benchmarks, classifying them into three generations. Reporting SRs over the period from 2008 to 2012, she outlines the advantage of second and third generation indices over their first generation counterparts. However, she does not address their diversification benefits in a portfolio setting, nor does she provide significance tests for the obtained results.

This article aims to fill the gap by evaluating the diversification benefits of seven different commodity indices - covering all three index generations - for a traditional U.S. investor from June 1991 to May 2013. The article extends the existing body of literature in various ways: first of all, to the best of my knowledge, it is the only study that considers third generation indices in a portfolio setting for a traditional U.S. investor and analyzes their benefits in an OOS setting. While earlier generation indices are exhaustingly analyzed, evidence for later generations is lacking. Moreover, by using a time span of 22 years, the study extends prior surveys like those of Miffre [2012] or Rallis, Miffre, and Fuertes [2012]. Finally, evaluating the risk-return performance of the commodities in an OOS setting provides further insights on the potential diversification benefits.

To evaluate the impact of the commodity indices, Lagrange Multiplier- (LM), Likelihood Ratio- (LR) and Wald-Tests (W) are performed to test statistically for mean-variance spanning, including a spanning test based on the Generalized Method of Moment (GMM) to account for conditional heteroskedasticity [Erb and Harvey, 2006]. Additionally, a step-down approach is used to characterize the source of a possible rejection. To test the commodity index performance in an OOS setting, a fixed rolling window approach is considered and significance tests according to Jobson and Korkie [1989] and Gibbson, Ross, and Shanken [1989] are performed.

Using spanning tests, the results show that after accounting for non-normality, first generation indices do not provide any benefits in terms of portfolio diversification, or in providing an improved tangency portfolio. The evidence for second generation indices is mixed, while third generation indices exhibit benefits in terms of both higher returns and lower volatility. The OOS analysis confirms these results. Later generation indices, clearly increase the OOS Sharpe ratios and reduce the expected shortfall for all considered window sizes. On the other hand, first generation benchmarks show non-persistent performance with some improved and some degraded portfolios. Overall, the investor should consider indices with trading strategies rather than simple long-only benchmarks. Companies should possibly follow multidimensional weighting and allocation schemes to improve their benchmark's performance.

Methodology and Hypothesis Building

The increasing doubts of the recent past challenge the reported diversification benefits of commodities and make it fair to ask whether those benefits still exist in today's financial markets. As already stated above, commodities are said to be influenced by factors different from those of equity or bond markets. Additionally, firms that use commodities as an input factor face increased costs and uncertainty when input prices rise [Chong and Miffre, 2010]. This adverse behavior leads to the often-reported low or even negative correlation values [see e.g. Gorton and Rouwenhorst, 2006; Erb and Harvey, 2006]. Nevertheless, this benefit is under attack by increased derivative market activity [Domanski and Heath, 2007]. The resulting financialization describes an environment where the equity and commodity markets becomes more integrated. Commodities are no longer only prone to their market-specific factors, but also to investors' behavior and equity market fundamentals. This leads to higher correlation values with other asset classes and to a time-varying volatility. In short, these volatility spillovers could result in reduced diversification benefits [Silvennoinen and Thorp, 2012]. The investor is thus left with the question: "Do diversification benefits in commodity markets still exist?"

Trying to answer this question, some studies have incorporated first generation indices such as the GSCI or the DJUBSCI into portfolios. Since these benchmarks are the most widely traded indices, a possible financialization caused by index investors may be more present in these benchmarks [Yau et al., 2007]. It is thus reasonable to include later generation indices in the analysis. However, evidence for these benchmarks is lacking. The only study evaluating enhanced benchmarks is the one by Miffre [2012], who does not analyze them within a portfolio environment. Yet, the performance in a portfolio setting is closer to the reality, since investors see commodities as an additional asset class for diversification, rather than as a standalone investment [Gorton and Rouwenhorst, 2006].

The analysis above raises the following questions: "Which generation of commodity indices still provides diversification benefits for a traditional U.S. investor?" and "What is the source of potential portfolio improvements?" The reported evidence with regard to trading strategies, provided by Erb and Harvey [2006], Miffre [2011], Miffre and Rallis [2007] and Fuertes, Miffre, and Rallis [2008] expects later generation indices, which follow momentum, term structure, or fundamental rules, to outperform their first generation counterparts and to provide benefits where the earlier indices may be lacking. Using these enhanced strategies, it is possible to weight the index away from poorly performing futures contracts. Finally, it is necessary to evaluate the performance of the commodities also in an OOS setting. While the commodities may show a superior performance in-sample (IS), practitioners are more concerned about the ex-ante setting. The question is thus: "Does the IS performance of the commodity indices also hold in an OOS setting?"

To evaluate the performance of the different commodity indices, first of all, the method of mean-variance spanning is used. Mean-variance spanning was introduced by Huberman and Kandel in 1987 [DeRoon and Nijman, 2001] and analyzes whether adding a set of N test assets significantly improves the initial efficient frontier, consisting of only K benchmark assets. If the new frontier, represented by the set of N+K assets, and the initial frontier coincide, there is spanning. In this case, no mean-variance optimizer can improve its portfolio by including the test assets in its investment universe [DeRoon and Nijman, 2001].

Formally, spanning tests are based on the idea of regressing the test assets on the benchmark assets. Given that the test asset only consists of one index at a time, the final regression equation is given by:

$$R_{com} = \propto + \beta_{U.S.Equity} R_{U.S.Equity} + \beta_{U.S.Bond} R_{U.S.Bond} + \epsilon \quad (1)$$

where R_{com}, $R_{(U.S.Equity)}$ and $R_{(U.S.Bond)}$ are (T×1) vectors of excess returns and ε represents the error term. Kan and Zhou [2012] state that the regression for the statistical tests can be performed using both total and excess returns. Since the investment universe also includes a risk-free asset, using total return data would mean including this rate as an independent regressor. Daskalaki and Skiadopoulos [2011], however, stress that this is undesirable, because the asset tends to exhibit persistency. Thus, excess returns over the risk-free rate are constructed. Hubermann and Kandel [1987] state the null hypothesis for spanning as:

$$H_0: \alpha = 0, \delta = 1 - \beta = 1 - \beta_{U.S.Equity} - \beta_{U.S.Bond} = 0 \quad (2)$$

Economically, this means that failing to reject the null, the universe of (K+1) assets does not improve the tangency portfolio $\propto = 0$, nor does it have a positive effect on the Global Minimum Variance Portfolio (GMVP) (δ=0). Since (2) is a joint hypothesis, the null states that both frontiers coincide and that including additional assets into the investment universe does not shift the efficient frontier [Belousova and Dorfleitner, 2012].

Assuming a normal distribution of returns, the critical values of the LM-, LR- and W-statistics are computed. All tests are asymptotically chi-squared distributed with two degrees of freedom. For finite samples, Berndt and Savin [1977] and Breusch [1979] show that $W \geq LR \geq LM$ holds. As a consequence, the W test favors rejections, while the opposite is true for the LM test. Hence, to obtain reliable results, all three tests should be performed [Belousova and Dorfleitner, 2012].

Since the academic literature reports a presence of nonnormality in commodity future returns [see e.g. Erb and Harvey, 2006; Jensen and Mercer, 2011], but the three tests are based on the assumption of a normal distribution, the presence of conditional heteroskedasticity leads to invalid results for the three test statistics. In this case, the tests are no longer asymptotically chi-squared distributed [Belousova and Dorfleitner, 2012; Kan and Zhou, 2012].

Exhibit 1 reports the p-values for the Engle [1988] test for conditional heteroskedasticity of the residuals. Since the dataset rejects the null of "no conditional heteroskedasticity" for some variables, the analysis is complemented by the Wald test introduced by Ferson, Foerster, and Keim [1993]. The three authors developed the test by using the GMM approach introduced by Hansen [1982]. The only difference is that the GMM Estimator is used instead of the MLE [Belousova and Dorfleitner, 2012].

Furthermore, Kan and Zhou [2012] outlined that particular attention has to be paid when using the joint hypothesis in (2). Since the GMVP can be estimated more accurately than the tangency portfolio, the test is biased towards (δ=0). This gives rise to potential divergence discrepancy between economic and statistical significance. Given that a small change in the GMVP is statistically easy to detect, it is not necessarily important in economic terms. Furthermore, a difference in the tangency portfolio might be economically very important, yet will be difficult to detect statistically [Kan and Zhou, 2012]. Kan and Zhou [2012] proposed a step-down procedure that aims to resolve these problems. They created two distinct F-tests with the following hypotheses:

$$H_{0,F1}: \alpha = 0 \qquad (3)$$

$$H_{0,F2|\alpha=0}: \delta = 0 \qquad (4)$$

Failing to reject (3) states that the two tangency portfolios are statistically similar, while (4), conditional that (3) holds, shows that the two GMVP are statistically not dissimilar. The two F-tests are given by:

$$F_1 = (T - K - 1)\left(\frac{\bar{\Sigma}}{\hat{\Sigma}-1}\right) \qquad (5)$$

$$F_2 = (T - K)\left(\frac{\tilde{\Sigma}}{\bar{\Sigma}-1}\right) \qquad (6)$$

where $\hat{\Sigma}$ is the unconstrained and $\bar{\Sigma}$ is the constrained, when α=0, MLE of Σ. Further $\tilde{\Sigma}$ is the constrained estimator when both α=0 and δ=0 hold. Under H_0, the F-test in (5) follows a F-distribution with 1 and (*T-K-1*) degrees of freedom. The test in (6) follows the same distribution, but with 1 and (*T-K*) degrees of freedom.

Complementing the analysis with the step-down approach leads to a higher degree of information, regarding the impact commodities have on a traditional portfolio. First of all, it is possible to determine the source of a possible rejection in (2). This is either due to the change in the GMVP or because of an improved tangency portfolio. Second, it is possible to solve the problem of divergence in economic and statistical significance by setting different significance levels for the two tests [Kan and Zhou, 2012].

Finally, since practitioners are mostly concerned with the out-of-sample performance of their investments, the analysis is contemplated with a fixed rolling window approach. Given a time series of length *T*, a rolling window of size Z, where $Z \geq T$, and any point in time *t*, we use the last *Z* return observations to compute the mean-variance efficient portfolio weights. These weights are then used to construct optimal portfolios and to extract the resulting OOS returns for the time interval [*t*,*t*+1]. This process is repeated, by incorporating the observation from *t*+1 and ignoring the earliest one. In total, this approach allows to compute (*T-Z*) optimal mean-variance OOS portfolio returns, which are then used to construct performance measures including Sharpe ratios, total turnover, expected shortfall, as well as general descriptive measures. First, these steps are taken for the base portfolio and then for the seven other portfolios, always including one commodity index at a time. To ensure robust results, different window sizes are used, including: *Z* = 36,48,60,and 72. To account for significance, I further incorporate the approach by Jobson and Korkie [1989] and Gibbson, Ross, and Shanken [1989], who test the null hypothesis of whether or not there is a difference between the SRs of two portfolios.

Data

Monthly return data are obtained from Bloomberg covering a 22-year period from June 1991 to May 2013 (264 observations). Exhibit 1 provides summary statistics of the indices, including an overview of their individual construction methodologies. The data cover the S&P 500, representing the U.S. Stock Market, a 3-month U.S. Treasury (T-Bill) serving as an indicator for the risk-free rate and the Barclays Capital U.S. Aggregate Bond Index (BARC), representing fixed income securities. The BARC was created in 1986 and includes Treasuries, Government and Corporate Bonds, as well as mortgage-backed securities. It also includes high yield and emerging market bonds traded in the United States [Barclays, 2012]. With regard to the commodities, data on seven indices from the different generations were obtained. All indices represent total return indices, classified according to Miffre [2012].

The GSCI and the Dow Jones-UBS Commodity Index (DJUBSCI) are two of the most widely used commodity indices in the academic literature and do not include any trading strategies [Yau et al., 2007]. Both are long-only indices. The GSCI was launched in 1991 and currently invests in twenty-four futures from five commodity classes including Energy, Industrial Metals, Precious Metals, Agriculture and Livestock. The main criterion to be included in the GSCI is the average world production over the last five years. To prevent unimportant commodities being included in the index, a minimum contribution to world production is necessary.

While the GSCI has a higher exposure to the Energy sector (around 70%), the DJUBSCI is more diversified across the different commodity sectors. Created in 1998 and backfilled with data until 1990, it currently covers twenty future contracts from various commodity sectors. The DJUBSCI uses both world production and liquidity to classify investable commodities. Moreover, special weight requirements apply: no sector should exceed 33% of the index weights, and the weight for individual futures is a minimum of 2% and a maximum of 15%. The DJUBSCI is reweighted on an annual basis, while the GSCI remains fixed [GSCI, 2013; DJUBSCI, 2013a; DJUBSCI, 2013b; Daskalaki and Skiadopoulos, 2011; Erb and Harvey, 2006].

Later generation indices are characterized by specialized rolling, selecting, or reweighing methodologies. Both the GSCI and the DJUBSCI hold liquid contracts that lie on the front end of the term structure. They roll from the front to the second nearest contract. The problem is that first generation indices always assume a backwardated market. In markets characterized by high inventory costs and an upward sloping term structure (a market in contango), these indices perform poorly. Second generation indices try to solve this problem

Asset	Construction Methodology	Annual Mean (%)	Annual Volatility (%)	Sharpe Ratio	Skewness	Excess Kurtosis	Min. Return	Max. Return	Jarque-Bera p-Values	Engle p-Values
Base Portfolio										
S&P 500	Market Cap	10.13	14.83	0.48	-0.63	1.27	-16.79	11.44	0.001	---
Barclays	Market Cap	6.62	3.70	0.98	-0.28	0.86	-3.36	3.87	0.0118	---
1st Generation										
GSCI	Long Only	5.38	21.00	0.11	-0.37	1.84	-28.19	19.67	0.001	0.0026
DJUBS	Long Only	5.84	15.03	0.19	-0.57	2.61	-21.28	13.00	0.001	0.0029
2nd Generation										
ML	Semi Continuous Rolling	11.50	20.01	0.43	-0.27	2.13	-26.57	21.71	0.001	0.0659
MSLF	Momentum Long/Flat	9.30	10.66	0.59	0.07	2.54	-10.12	11.42	0.001	0.0002
3rd Generation										
CYD	Term Structure	7.55	8.33	0.55	-0.24	1.79	-11.20	7.90	0.001	0.7928
MSLS	Momentum Long/Short	7.33	10.93	0.40	0.21	1.91	-10.89	11.62	0.001	0.0039
SH	Fundamental/Rule Based	14.96	14.06	0.85	-0.81	4.73	-22.60	13.96	0.001	0.0014
T-Bill	-	2.99	0.5	---	-0.23	-1.47	0.000	0.005	0.001	---

The exhibit reports the descriptive statistics on total return data over the period June 1991–May 2013 for each individual asset. From column 2 to 10: constructing methodology, annual mean, annual volatility, Sharpe ratio, skewness, excess kurtosis, minimum return, maximum return, and the p-values for the Jaruqe-Bera Test and the Engle Test. Sharpe ratios are computed using annual mean, annual volatility and the annual mean of the 3-month U.S. Treasury Bill as the risk free rate. To test for normality of the returns, Jarque-Bera p-values are reported. Engle p-values, capture whether the residuals from the regression specified in (1) are prone to conditional heteroskedasticity. The null of the former states that the series follows a normal distribution and the null of the latter assumes no conditional heteroskedasticity of the residuals.

Exhibit 1 Descriptive Statistics for the Period May 1991–June 2013

Source: Bloomberg

by considering the whole term structure of the future contract Miffre [2012]. With regard to this family, the article focuses on the Merrill Lynch Commodity Index eXtra (MLCX) and the Morningstar Commodity Index Long/Flat (MSLF).

The MLCX follows a semi-continuous roll scheme, meaning that it rolls from the second to the third month future contract. As of today, the MLCX invests in more downstream commodities, such as gasoline or live cattle. All commodities are selected based on liquidity and importance for the global economy [Lynch, 2006].

The MSLF follows a momentum-long-flat strategy. Next to rolling into future contracts that lie further apart on the term structure, the index also considers the past performance of the future contracts. If a commodity exceeds its 12-month moving average, the index takes the long position. The flat positions are equal to holding cash. These investments are implicitly derived from the short positions of the Morningstar Long/Short Commodity Index (MSLS), which are also determined on the basis of the 12-month moving average. Thus, while the MSLS takes both investment sides, the MSLF replaces the short positions with flat positions. The MSLS also follows a momentum strategy.

With its long and short positions, the MSLS characterizes the third generation of commodity indices. These benchmarks try to enhance their performance by going long into commodities currently facing a backwarded market and going short in future contracts with contangoed markets. As a result, they are said to perform well in good and bad market environments Miffre [2012]. The MSLS currently consists of Energy (39.30%), Metals (13.90%), Agriculture (38.40%), and Livestock (8.40%) futures. The maximum load of a futures contract is 10%, with monthly rebalancing, dependent on the moving average [Morningstar, 2013]. The CYD Long/Short Commodity Index (CYD) is a Term Structure Index, meaning that long and short positions are determined by the shape of the term structure, whereby long positions are taken for the most backwarded commodities and short positions for the most contangoed futures. The CYD currently consists of Cereals (21.74%), Meat and Livestock (13.04%), Energy (26.09%), Metals (21.74%), and Exotics (17.39%), including Cocoa, Coffee, or Sugar [CYD, 2013].

Finally the Summerhaven Dynamic Commodity Index (SDCI) is a fundamental rule-based index. The benchmark includes forecasts of fundamental factors, as well as technical signals or price signals to determine the optimal commodity weights. As of 2013, the SDCI consisted of 14 out of 27 eligible commodity futures, including sectors like Industrial Metals, Precious Metals, Energy, and Agriculture, that are rebalanced every month [Miffre, 2012; Summerheaven, 2013].

Analyzing the reported annual means and standard deviations from Exhibit 1, no clear picture emerges. While first generation indices show both a lower mean and a higher standard deviation, the results for second and third generation indices are inconsistent. Both higher means with lower volatility and lower means with higher volatility co-exist.

Asset	S&P 500	Barclays	GSCI	DJUBS	ML	MSLF	CYD	MSLS	SH	T-Bill
S&P 500	1	-	-	-	-	-	-	-	-	-
Barclays	0.0714	1	-	-	-	-	-	-	-	-
GSCI	0.2468*	0.0155	1	-	-	-	-	-	-	-
DJUBS	0.3119*	0.0391	0.8972*	1	-	-	-	-	-	-
ML	0.2489*	-0.0002	0.9745*	0.9231*	1	-	-	-	-	-
MSLF	0.0792	-0.0253	0.7443*	0.7838*	0.7488*	1	-	-	-	-
CYD	-0.2087*	0.0119	0.0752	-0.0206	0.0375	0.3107*	1	-	-	-
MSLS	-0.1054	-0.0641	0.5269*	0.4838*	0.5160*	0.8715*	0.4568*	1	-	-
SH	0.2933*	0.0068	0.7569*	0.8762*	0.7810*	0.7788*	0.0733	0.4892*	1	-
T-Bill	0.0497	0.0841	0.0473	0.0631	0.0682	0.0747	0.1362**	0.1103	0.0875	1

The table reports Pearson's correlation coefficients for each asset. Significance tests were performed using a standard t-test.

* Significant at 1%; ** Significant at 5%.

Exhibit 2 Correlation Matrix for the Period May 1991–June 2013

Source: Author's calculations & Bloomberg

Comparing SRs, it can be seen that the fixed income securities exhibit the highest value with 0.98. First generation indices are dominated by both equity and bond indices. Again, the evidence for later generation indices is mixed. For the second generation, only the MSLF shows superior performance over equities, while in the third generation only the CYD and the SDCI exhibit higher risk-return performance compared to the S&P 500. Comparing SRs across the different commodity indices, first generation indices are dominated by second and third generation indices. This observation is in line with reported evidence by Miffre [2012]. Contradictory results are found for second and third generation indices. The latter does not necessarily outperform the former: The SR for the MLCX (0.43) and MSLF (0.59) are both higher than for the CYD (0.55) and the MSLS (0.40). Finally, the highest SR is reported for the SDCI (0.85), indicating the benchmark as the best standalone investment in comparison to the other commodity indices.

Looking at the return distributions, all indices exhibit positive excess kurtosis. This implies a leptokurtic return distribution, meaning the curve shows fatter tails and a higher probability for extreme events compared to a normal distribution [Belousova and Dorfleitner, 2012]. Furthermore, the majority of indices report negatively skewed return distributions. Exceptions are the MSLF and the MSLS. This contradicts findings from Jensen and Mercer [2011] and Erb and Harvey [2006], but is in line with the mixed evidence reported by Miffre [2012]. The two exceptions (MSLF and MSLS) go in hand with the same rebalancing methodology. Both select their commodities on the basis of the 12-month moving average. Thus futures are only included if they exceed this average, or will be otherwise considered as short or flat positions. This could explain the positive skewness. Also reported are the p-values of the Jarque-Bera test for normality. All assets reject the null of a normal distribution at the 5% significance level. Exhibit 2 shows the Correlation Matrix for the entities in Exhibit 1, a subject to which we will return later.

Empirical Analysis
Commodity Index Performance from 1991–2013

Exhibit 3 reports the results of the mean-variance spanning tests, including the GMM-Wald and the step-down procedure. As noted earlier, Kan and Zhou [2012] state that it is statistically more difficult to detect a change in the tangency portfolio. To accurately interpret the results of the F1-Test, p-values that slightly exceed the 10% significance level will still be considered as a rejection of the null hypothesis.

Concerning first generation indices, the GSCI fails to reject the joint hypothesis of mean-variance spanning at the 5% and 10% significance level. Also, after accounting for non-normality, no diversification benefits are reported. On the other hand, the DJUBSCI rejects the null of mean-variance spanning at the 5% significance level. Accounting for non-normality, this result becomes insignificant.

Evidence for second generation indices show that the MLCX fails to reject the null hypothesis of mean-variance spanning at the 5% significance level. This result is underlined when accounted for non-normality. On the other hand, the MSLF shows a significant improvement in the efficient frontier, which also holds under non-normality of returns. The step-down procedure states that this positive change is due to both an improvement in the tangency portfolio and the GMVP.

Considering the third generation, all indices reject the null of mean-variance spanning, even when accounting for non-normality. Additionally, the step-down procedure shows that including third generation indices in an otherwise diversified portfolio will lead to an improved tangency and GMVP at the 5% significance level.

Out-of-Sample Performance of Commodity Indices

Exhibit 4 shows the results of the OOS performance tests for the different portfolios over the various windows sizes. Comparing the SRs of the base portfolio and those including first generation indices, no clear picture emerges. For the different window sizes, some portfolios show an increased SR, while others show inferior performance. Evidence is clearer for later generation indices. Here, benchmarks from both families improve the SRs, for all considered window sizes. The largest increase of all benchmarks is always reported for the CYD, and accounts for an improvement of approx. 13%. For the second generation, the MSLS performs best and accounts for an increase of around 9%.

The same pattern is also reflected in the values of the expected shortfall. Here, second and third generation indices lead to a reduction in the measure of maximal loss that the investor encounters. Again, for the first generation, these values vary, depending on the third and fourth moment of the return distribution.

While the overall picture shows an improvement due to commodity indices, especially when considering later generations, only some of the results are statistically significant. Exhibit 4 shows that of the 32 portfolio SRs analyzed, only 12 are significantly different from the base portfolio. Nearly half of the ones that are significant belong to the first generation. Since this includes SRs that are higher and lower than the base portfolio, we can conclude on the varying benefits of these benchmarks. With regard to the second generation, only the MLCX shows a significant improvement for Z=72. Thus, one has to be careful in concluding on the diversification benefits of second generation indices. The rest of the significant measures belong to the third generation, which supports their diversification benefits.

Discussion

The empirical results provide room for interpretation and fund allocation recommendations for a traditional U.S. investor. Over the whole period from May 1991 to June 2013, first generation indices will no longer provide the investor with benefits. The two benchmarks employed fail to reduce the portfolio volatility, or only exhibit varying OOS-SRs. This lack in performance is in line with the research of Daskalaki and Skiadopoulos [2011], and contrasts the findings of Belousova and Dorfleitner [2012] and Galvani and Plourde [2009], who rely on individual future contracts. Looking at Exhibits 1 and 3, the GSCI rejects the null at a higher significance level than the DJUBSCI. This might be due to the much higher volatility, given the nearly equal level of return for both indices. In the end, the investor is better off not to allocate his funds towards these benchmarks. With regard to second generation indices, the investor should consider momentum strategy indices to improve its investment universe. The results can be explained by the high SR and the low correlation values. Looking at Exhibits 1 and 2, the MSLF reports one of the highest SRs among the indices. The low and even negative correlation values, especially with the fixed income index, marks the source of the diversification benefits. Furthermore, it can be seen that benchmarks like the MLCX, which just rolls into the second nearest future contracts rather than front end contracts, will not reduce the overall volatility, nor enhance portfolio return. Obviously, indices need to provide more enhanced construction methodologies.

This argument is supported when looking at the third generation. All three indices provide benefits for the in-

Commodities		LM	LR	Wald	GMM-Wald	F1	F2
1st Generation	GSCI	3.9645	3.9946	4.0249	2.8540	0.0000	3.9944
		(0.1388)	(0.1388)	(0.1388)	(0.2458)	(0.9933)	(0.0467)
	DJUBS	6.7324	6.8197	6.9085	5.6842	0.0124	6.8435
		(0.0344)	(0.0344)	(0.0344)	(0.0620)	(0.9115)	(0.0094)
2nd Generation	ML	5.9019	5.9689	6.0369	3.8737	1.9419	4.0119
		(0.0523)	(0.0523)	(0.0523)	(0.1494)	(0.1646)	(0.0462)
	MSLF	30.0814	31.9377	33.9498	51.8200	6.1158	26.9225
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0140)	(0.0000)
3rd Generation	CYD	48.5552	53.6565	59.4982	59.2415	7.2785	50.3372
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0074)	(0.0000)
	MSLS	40.0690	43.4574	47.2388	63.9214	8.5804	37.0496
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0037)	(0.0000)
	SH	15.9220	16.4223	16.9439	8.6864	9.7537	6.7714
		(0.0003)	(0.0003)	(0.0003)	(0.0146)	(0.0020)	(0.0098)

The table reports the test statistics and p-values (in brackets) for the Lagrange Multiplier (LM)-, the Likelihood Ratio (LR)-, and the Wald-Test, as well as for the Wald Test using the generalized Method of Moments Approach (GMM-Wald). Under the null the test asset spans the same universe as the benchmark assets. Also included are the results for the two F-Tests of the Step-Down Procedure. Here F1 evaluates the ability of the test assets to increase the overall return, while F2 tests for an overall reduction of risk. For all computation monthly excess return data over the 3-month U.S. Treasury Bill was used covering the period from June 1991 to May 2013.

Exhibit 3 Results of Spanning Tests for Commodity Indices (1991–2013)

Source: Author's calculations

vestor and should have been included in the portfolio. Again, they all report very high SR together, with low or negative correlation values. The beneficial strategies include fundamental, momentum, and term-structure methodologies. This result is in line with Erb and Harvey [2006], Miffre [2011], Miffre and Rallis [2007], and Fuertes, Miffre, and Rallis [2008], who utilize these strategies with individual future contracts.

The same conclusion can be drawn when looking at the results of the OOS performance. The reported evidence is in line with the studies from You and Daigler [2012] and Bessler and Wolf [2014] and partly contradicts the findings of Daskalaki and Skiadopoulos [2011]. While Daskalaki and Skiadopoulos [2011] report reduced SRs when commodity indices are included, our analysis shows the opposite. Nevertheless, only some of the reported SRs are also statistically significant, which should be treated with caution.

How can the observed differences between the three index families be explained? Obviously all indices that fail to reject the null of mean-variance spanning do not follow a rolling technique that includes the whole term structure of future prices, nor do they take short positions. As already noted, first generation indices suffer from the fact that they assume the market is always in backwardation. The MLCX tries to solve this problem by considering future contracts that lie further apart on the term structure curve, but only rolls from the second to the third month contract, as opposed to considering the whole curve. The problem of contracts closer to maturity is that they tend to be more in contango than more distant contracts [Miffre, 2012]. This would subsequently lead to lower returns for these indices.

Moreover, the considered dataset covers bullish and bearish market periods. The commodity boom from 2005 to 2008 is included, but the recent financial crisis from 2007 to 2009 is as well. In particular, the last period was characterized by one of the largest economic recessions since the Great Depression of the late 1920s. Today, agriculture prices still remain below their previous peaks in the 1970s [Dwyer, Gardner, and Williams, 2011]. Oil as a major part of the energy sector was in contango from late 2004 to 2009 [Domanski and Heath, 2007]. For long-only indices, like the DJUBSCI, the GSCI, or the MLCX, this time was associated with negative roll returns. Later generation commodity indices may have improved their returns during these contangoed markets by weighting towards better performing future contracts, or by going short. This explanation would be in line with reported evidence from Miffre [2012], Erb and Harvey [2006] and Rallis, Miffre, and Fuertes [2012], who show that long-short, momentum, or enhanced rolling techniques improve the overall return when compared to long-only strategies. Furthermore, indices that roll into mid- to far-end future contracts may incur a liquidity risk premium, since these futures are less liquid than front contracts [Rallis, Miffre, and Fuertes 2012]. The DJUBSCI and the MLCX, on the other hand, select futures on the basis of liquidity. Thus they may not have earned this source of return.

With regard to a possible diversification benefit, futures close to expiration are more volatile because they are more prone to supply and demand shocks [Miffre, 2012]. This would explain the high standard deviations, reported for the three indices in Exhibit 1. Additionally, Miffre [2011] reports that during phases of economic turmoil long-short strategies tend to provide lower correlations than long-only indices. Indeed, when looking at Exhibit 2, all three indices show significantly high correlation values compared to the other indices. Yet the same level of correlation is also reported for the SDCI, which reports benefits. An explanation could be that for a commodity index to be beneficial in terms of the joint hypothesis in (2), it not only has to provide diversification benefits, but also must have a high return. Truly, when looking at the SR, the SDCI reports the highest value among the commodity indices. Having a look at the associated means and standard deviations from Exhibit 4, we can see that the reported gains mostly stem from a reduction in risk, rather than from improved returns. This underlines the diversification character of the commodity indices.

Finally, it can be asked whether the obtained results are a sign for an increased financialization of the commodity markets. The answer to this question is: "Maybe." One has to be careful in linking the obtained results to the effects of financialization. This article does not cover the analysis to conclude whether there are increased cross-sectional correlations or volatility spillovers from traditional asset markets or not. Nevertheless, Tang and Xiong [2012] argue that the increased index investment since the early 2000s has led to rising correlations among commodity futures, especially in indices like the GSCI and the DJUBSCI. This in turn has diminished the diversification benefits of these benchmarks. Indeed, the results show that first generation indices no longer provide any benefits IS and mixed results OOS. Additionally, when looking at Exhibit 1, the correlation among the commodity indices is mixed, but is mostly high and positive. However, these values are also reported for later generation indices, which still yield benefits to investors. It might be tempting to assume that financialization is an explanation for the observed results, but as the debate of whether it is a cause of increased correlation and volatility is still going on, it only

	Portfolio		Sharpe Ratio	Average Return	Standard Deviation	Skewness	Kurtosis	Expected Shortfall(5%)	Total Turnover
Z= 36	*Base Portfolio*		*0.4814*	*0.0644*	*0.1338*	*-0.1845*	*35.810*	*-0.2355*	*0.0089*
	+ 1st Generation	GSCI	0.4729	0.0630	0.1333	-0.3185	39.342	-0.2399	0.0139
		DJUBS	0.4813	0.0625	0.1300	-0.2305	37.905	-0.2309	0.0169
	+ 2nd Generation	ML	0.4874	0.0648	0.1329	-0.2764	38.220	-0.2343	0.0144
		MSLF	0.5329	0.0638	0.1198	-0.1615	34.188	-0.1994	0.0192
	+ 3rd Generation	CYD	0.5580*	0.0673	0.1207	-0.1091	33.536	-0.1951	0.0220
		MSLS	0.5446*	0.0661	0.1214	-0.1194	29.887	-0.1921	0.0210
		SH	0.5391*	0.0683	0.1267	-0.2910	38.391	-0.2178	0.0168
Z=48	*Base Portfolio*		*0.4877*	*0.0650*	*0.1332*	*-0.1855*	*36.006*	*-0.2349*	*0.0092*
	+ 1st Generation	GSCI	0.4779*	0.0636	0.1332	-0.3169	39.362	-0.2395	0.0150
		DJUBS	0.4866	0.0630	0.1295	-0.2374	38.246	-0.2297	0.0177
	+ 2nd Generation	ML	0.4921	0.0653	0.1326	-0.2761	38.417	-0.2336	0.0154
		MSLF	0.5370	0.0640	0.1192	-0.1512	34.405	-0.1980	0.0201
	+ 3rd Generation	CYD	0.5599	0.0673	0.1203	-0.0995	33.890	-0.1950	0.0237
		MSLS	0.5432*	0.0657	0.1209	-0.0923	30.496	-0.1911	0.0218
		SH	0.5478*	0.0692	0.1263	-0.3008	38.838	-0.2166	0.0174
Z=60	*Base Portfolio*		*0.5161*	*0.0659*	*0.1276*	*-0.2006*	*34.239*	*-0.2216*	*0.0069*
	+ 1st Generation	GSCI	0.5202**	0.0656	0.1261	-0.2047	33.252	-0.2164	0.0108
		DJUBS	0.5179**	0.0636	0.1228	-0.2118	34.209	-0.2158	0.0137
	+ 2nd Generation	ML	0.5306	0.0668	0.1259	-0.1882	32.909	-0.2149	0.0113
		MSLF	0.5842	0.0665	0.1138	-0.2224	33.033	-0.1817	0.0147
	+ 3rd Generation	CYD	0.5973	0.0694	0.1162	-0.2305	33.837	-0.1898	0.0181
		MSLS	0.5878	0.0686	0.1168	-0.2196	31.530	-0.1906	0.0158
		SH	0.5795*	0.0689	0.1189	-0.2798	34.755	-0.1998	0.0124
Z=72	*Base Portfolio*		*0.5023*	*0.0655*	*0.1304*	*-0.2753*	*37.082*	*-0.2286*	*0.0050*
	+ 1st Generation	GSCI	0.5018*	0.0651	0.1298	-0.2771	36.137	-0.2256	0.0088
		DJUBS	0.5115*	0.0643	0.1258	-0.3087	38.059	-0.2238	0.0107
	+ 2nd Generation	ML	0.5185*	0.0669	0.1291	-0.2755	36.105	-0.2236	0.0092
		MSLF	0.5522	0.0650	0.1177	-0.2775	36.977	-0.1915	0.0122
	+ 3rd Generation	CYD	0.5839	0.0697	0.1194	-0.2347	35.853	-0.1935	0.0143
		MSLS	0.5596	0.0668	0.1194	-0.2365	33.893	-0.1942	0.0129
		SH	0.5653	0.0687	0.1215	-0.3718	39.451	-0.2086	0.0104

The table shows the out of sample performance measures for the different portfolios using a window size of K= 36, 48, 60, and 72, respectively. Included are the Sharpe ratio, the average annual Return and Standard Deviation, the Skewness, the Kurtosis, the Expected Shortfall, and the Total Turnover. Significance of the Sharpe ratio was tested according to Jobson and Korkie [1989] and Gibbson, Ross, and Shanken [1989]. The null hypothesis is whether there is no difference between the SR of the base portfolio and one that includes a commodity index. *Significant at 1%. ** Significant at 5%.

Exhibit 4 Out-of-Sample Performance of Commodity Indices (1991–2013)

Source: Author's calculations

provides a possible explanation for the observed results, rather than a final conclusion.

Conclusion

With commodity indices, the investor is able to gain exposure to a broad basket of commodity sectors. Since the launch of the GSCI, constant developments in the area of trading strategies, weighting, and rolling techniques have led to the development of a contemporaneous third generation of commodity indices. This increasing number of investment possibilities and the ever-increasing doubts about possible financialization make it more difficult for investors to choose among these benchmarks. To shed light on the issues, this article extends the prior research by formally comparing the three currently existing index families.

Using mean-variance spanning and including the first generation indices separately into a traditional U.S. portfolio over the period from May 1991 to June 2013, it can be seen that these indices no longer provide benefits to investors. The evidence for second generation indices is mixed: while long-only indices fail to improve the efficient frontier, momentum strategy indices should be considered as an investment, contributing to lower risk and higher returns. The latter point is also true for the third generation indices. Here, momentum, term-structure, and fundamental-based weighting strategies improve the efficient frontier. The same conclusion can be drawn in an OOS setting. While first generation indices show mixed results, later generation indices improve the SRs and reduce the expected shortfall. Although only some of the results are significant, the various window sizes all lead to the same picture.

These results challenge the existing literature and search for explanations in the different construction methodologies and the growing financialization of the commodity market. They show that trading strategies are an integral part for commodity indices. An investor should allocate his funds towards later generation indices to make use of their diversifying ability. Issuing companies should consider a multidimensional selection and weighting methodology in order to improve the performance of their indices and attract more investors.

With its active weighting and allocating characteristics, third generation indices also challenge commodity traders, public funds, and commodity pools. A comparison between these groups might provide further insights. In the situation where later generation indices perform equally well, investors could have an investment opportunity that provides active allocation at lower costs. That analysis is beyond the scope of this article and is left to future research.

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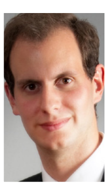

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