Long-Short Commodity Investing: A Review of the Literature

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Abstract

This article reviews recent academic studies that analyze the performance of long-short strategies in commodity futures markets. Special attention is devoted to the strategies based on roll-yields, inventory levels or hedging pressure that directly arise from the theory of storage and the hedging pressure hypothesis. Alternative strategies based on past performance, risk, value, skewness, liquidity or inflation betas are also studied, alongside with recent attempts to enhance performance by modifying or combining the original signals. Overall, the literature highlights the superiority of being long-short in commodity futures markets relative to being long-only.

Keywords: Commodities, Long-short strategies, Performance, Backwardation, Contango.

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1. Introduction

This article reviews recent empirical evidence on the performance of long-short strategies in commodity futures markets. First, the paper presents mainstream strategies based on signals such as roll-yields, inventory levels, hedging pressure or past performance and places the performance of these strategies in the context of the theories that underpin commodity futures pricing; namely, the theory of storage of Kaldor (1939), Working (1949) and Brennan (1958) and the hedging pressure hypothesis of Cootner (1960) and Hirshleifer (1988). Second, the article reviews other long-short strategies that attempt to generate good performance by modifying or combining the original signals or by tactically allocating wealth based on other criteria such as risk, value, liquidity, skewness, or inflation betas. The bottom line here is to argue that most of these long-short strategies performed better than long-only positions in the past decades.

It is hoped that this review will be timely to academics who are interested in pricing commodity futures and to long-short market participants such as commodity trading advisors and long-short index providers keen to design practical investment solutions in commodity futures markets.

The article is organized as follows. Section 2 reviews the long-short strategies that originate from the theory of storage. Section 3 covers the long-short strategies that emanate from the hedging pressure hypothesis. Section 4 focuses on commodity-based trend-following portfolios; these are less theoretically sound but their performance has nonetheless been shown to relate to the fundamentals of commodity futures pricing as highlighted by the theories of storage and hedging pressure. Section 5 pays special attention to alternative long-short signals based on risk, value, skewness or open interest. Section 6 documents that one can improve upon these basic frameworks by modifying or combining the original signals. Finally, Section 7 concludes.

2. Long-Short Strategies Originating in the Theory of Storage

I begin this review by presenting the theory of storage and the strategies based on roll-yields and inventory levels that are direct spin-offs of this theory.

2.1 The Theory of Storage

The theory of storage, as put forward by Kaldor (1939), Working (1949) and Brennan (1958), relates the basis, or the difference between the spot and futures prices of a commodity, to the cost of storage (transportation, warehousing and insurance costs), the interests foregone in purchasing the physical commodity and the convenience yield earned from owning the spot asset.

According to the theory of storage, a negative basis (also called roll-yield) or an upward-sloping term structure of commodity futures prices comes hand-in-hand with high inventories. Markets are then said to be in *contango*. In this scenario, the commodity is in abundant supply, inventory holders can buy it cheap in the spot market and sell it forward at a profit that compensates them for the costs incurred while storing and financing the asset. Assuming a constant spot price, the futures price of a contangoed contract is expected to decrease in value as maturity approaches, suggesting that a short position in a contangoed market is probably optimal. Alternatively, the theory of storage argues that the basis or roll-yield should be positive when inventories are low or in the event of a stock-out. The term structure of futures prices then slopes downward and markets are said to be in *backwardation*. Under this scenario, the commodity is expensive since it is scarce and the benefits of owning the physical asset (called convenience yield) exceed storage and financing costs. Again assuming a constant spot price, the futures price of a backwardated asset is deemed to appreciate with maturity, suggesting, this time around, that a long position is likely to be profitable.

In line with the theory of storage, Telser (1958) shows that the level of inventories is key to determining whether a market is backwardated or contangoed; backwardation occurs when inventories are low (namely, before harvest) and thus when convenience yield is high. Fama and French (1987) provide evidence in support of the role of interest rates and convenience yields as drivers of the basis. Backing for inventories as a factor that influences the basis is also provided in Fama and French (1988), Gorton, Hayashi and Rouwenhorst (2012) or Symeonidis, Prokopczuk, Brooks and Lazar (2012).

2.2 Trading Strategies Based on Roll-Yields or Inventories

It follows from the theory of storage that roll-yields and inventory levels shall be used as signals to capture the fundamentals of backwardation and contango and thus to model the risk premium present in commodity futures markets. Support in favor of this hypothesis is provided in Feldman and Till (2006) who show that the stronger the propensity of an agricultural commodity futures market to be in backwardation, the higher its performance. Gorton, Hayashi and Rouwenhorst (2012) document likewise that higher roll-yields come hand-in-hand with higher average excess returns. This suggests that roll-yields could be used as signal for asset allocation. Indeed, Erb and Harvey (2006) and Gorton and Rouwenhorst (2006) show that strategies that buy backwardated commodities with high roll-yields and short contangoed commodities with low roll-yields present Sharpe ratios that exceed those of long-only commodity portfolios.

As summarized in Table 1, Panel A,[1] many other authors have followed suite. Typically the methodology consists of *i*) modelling roll-yields as a function of the price differential between front and second nearest contracts, *ii*) basing the asset allocation on the most recent roll-yields, *iii*) allowing for equal weights in the constituents of the long-short portfolios, and *iv*) holding the positions for a month. While there are some slight differences in the number of commodities included in the long-short portfolios or in the samples and cross-sections considered, the main conclusion that emerges from these papers remains the same: long-short portfolios that trade on roll-yields offer a Sharpe ratio that is much higher than the one obtained on long-only commodity portfolios (be it an equally-weighted portfolio of all commodities or a commodity index such as the S&P-GSCI). This highlights the now common belief that investors benefit from taking long positions in backwardated markets and short positions in contangoed markets. Making the simplifying assumption that commodity futures markets are solely backwardated by being long-only seems suboptimal.

The theory of storage implies that either inventories or roll-yields could be used as a signal for asset allocation. The analogy between the two signals is highlighted in Gorton, Hayashi and Rouwenhorst (2012) who demonstrate that relative scarce commodities with low inventory levels present positive roll-yields. Vice versa, relatively abundant commodities with high inventory levels tend to exhibit negative roll-yields. This suggests that inventory levels could be used to tell whether a commodity futures is backwardated or contangoed and could thus serve as a long-short signal. As it appears, sorting commodities into portfolios based on their

[1] In the cited references, the long-short portfolios are either 100% or 50%-collateralized. Whenever possible, this review focuses on Sharpe ratios, and not on mean excess returns, as the former remain unchanged irrespective of the choice of collateralization, while the latter are sensitive to that choice.

levels of standardized inventory[2] provides an interesting spread in excess returns, with backwardated commodities with lower standardized inventories earning 3.45% per annum more than contangoed commodities with higher standardized inventories on a fully-collateralized basis (*t*-statistic for the difference = 2.78). On a risk-adjusted basis, the Sharpe ratio of such a long-short portfolio stands at 0.46 versus 0.38 for a long-only equally-weighted monthly-rebalanced portfolio of all commodities. Along the same line, Dewally, Ederington and Fernando (2013) show that differences in inventory levels explain differences in mean excess returns in the crude oil, gasoline and heating oil futures markets. As predicted by the theory of storage, the relationship between the two variables is found to be negative.

It is probably worth noting at this stage some of the difficulties encountered while collecting inventory data. Gorton, Hayashi and Rouwenhorst (2012), amongst others, argue that two issues could potentially plague the analysis of the relationship between inventory levels and the risk premium present in commodity futures markets. First, inventory data should be collected in relation to the delivery place of the underlying asset of the futures contract; such information might not be publicly available or easily accessible. Second, inventory data are likely to be revised after being published, making it difficult to implement trading strategies based on such signal. It follows that, when sorting commodities into backwardated and contangoed portfolios, it might be easier to bypass the complexity of gathering inventory data by using instead easy-to-collect market-based signals such as roll-yields.

[2] Standardized inventory is measured as the ratio of inventory to its 12-month moving average. The series is lagged by one-month to reflect upon the fact that inventory data are published with a lag.

3. Long-Short Strategies Emanating from the Hedging Pressure Hypothesis

In this section I review the strategies that originate from the normal backwardation theory and from the hedging pressure hypothesis, showing that the latter can be used to model the risk premium of commodity futures contracts.

3.1 The Normal Backwardation Theory

The theory of normal backwardation, formulated by Keynes (1930) and Hicks (1939), postulates that commodity futures markets exist to facilitate hedging. It is assumed that hedgers are net short; namely, the positions of producers who sell their output forward exceed the positions of consumers who purchase their input forward. Net short hedgers, willing to transfer their risk of a price decline to net long speculators, must entice them to take long futures positions. This is done by setting the futures price today below the spot price expected at maturity of the futures contract. In other words, futures prices are expected to rise as maturity approaches, so that net long speculators earn a positive risk premium for taking on the price risk that net short hedgers are willing to get rid of. The theory of normal backwardation thus provides a rationale for long-only commodity futures investments (*e.g.*, for holding long-only monthly-rebalanced portfolio of commodities or long-only commodity indices such as the S&P-GSCI or the CRB).

Empirical support in favor of the normal backwardation theory is at best weak. Tests implemented using traditional asset pricing models such as the CAPM refute the notion that markets are normally backwardated: standard asset pricing models show no evidence that speculators earn a positive risk premium in commodity futures markets (Dusak, 1973; Bodie and Rosansky, 1980; Baxter, Conine and Tamarkin, 1985; Kolb, 1996; Daskalaki, Kostakis and Skiadopoulos, 2013). Likewise, Kolb (1992) studies the actual price behavior of 23 commodity futures and concludes that “normal backwardation is not normal”: Only a few commodity contracts support the rising price pattern consistent with the Keynesian hypothesis. Evidence that long-only equally-weighted portfolios of commodities and long-only commodity indices perform worse than long-short portfolios on a risk-adjusted basis provide further evidence against the theory of Keynes (1930).

3.2 The Hedging Pressure Hypothesis

Noting that hedgers are not necessarily short, Cootner (1960) proposes a theoretical model, called the hedging pressure hypothesis, that allows for the possibility of net long, as well as net short, hedgers. As before with the normal backwardation theory, when hedgers are net short, the futures prices has to be set low relative to the spot price expected at maturity to entice speculators to take long futures positions. Vice versa, when hedgers are net long, the futures price has to be set high relative to the spot price expected at maturity to entice speculators to take short futures positions. As maturity approaches, the futures price of a backwardated/contangoed contract is expected to increase/decrease toward the expected spot price, enabling long/short speculators to earn a positive risk premium. It follows that if the hedging pressure hypothesis holds, speculators should be rewarded for taking long positions in backwardated contracts (when hedgers are net short) and short positions in contangoed contracts (when hedgers are net long).[3] Like Cootner (1960), Hirshleifer (1988) also endorses net hedging as an important driver of a commodity futures risk premium. He develops a theoretical model that accounts for trading costs and the non-marketability of producers' claims. He then shows that the risk premium earned on commodity futures depends on both

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[3] Hedgers' hedging pressure is typically defined as the difference between the numbers of short and long hedge positions divided by the total number of hedge positions. An alternative definition that amounts to the same inference on backwardation and contango uses the percentage of long hedge positions relative to total hedge positions. Data on the positions of large hedgers (or large commercial traders) and large speculators (or large non-commercial traders) are available in the aggregated commitment of traders report on the CFTC website.

systematic risk (as modelled by the CAPM beta) and idiosyncratic volatility conditional on net hedging.

While there is little support in favor of the theory of normal backwardation, empirical evidence has been brought forward in favor of the hedging pressure hypothesis of Cootner (1960) and Hirshleifer (1988). For example, Carter, Rausser and Smith (1983) support systematic risk and hedging pressure as determinants of a commodity futures risk premium by showing that long (short) speculators require an expected return above (below) the amount predicted by the security market line. Though recently questioned by Rouwenhorst and Tang (2012), the predictions of Hirshleifer's (1988) model were empirically validated in Bessembinder (1992) who shows that net hedging is an important determinant of commodity futures prices. De Roon, Nijman and Veld (2000) add to the conclusions of Bessembinder (1992) by saying that own-hedging pressure, as well as cross-hedging pressure, are key to explaining futures returns. Another interesting study in favor of the theory of Cootner (1960) was provided by Chang (1985) who uses a nonparametric test to show that a strategy that takes long (short) positions when large speculators are net long (short) is profitable in the corn, soybeans and wheat futures markets.

The hedging pressure hypothesis thus provides strong rationale for dynamic trading strategies that track the positions of speculators and hedgers. Basu and Miffre (2013) sort a cross-section of 27 commodity futures on the hedging pressure of large hedgers and/or large speculators and form long-short portfolios that buy the most backwardated commodities (for which hedgers are the shortest and/or speculators the longest) and sell the most contangoed commodities (for which hedgers are the longest and/or speculators the shortest). Such long-short portfolios earn an average Sharpe ratio of 0.51 over the period 1992-2011. By contrast, a long-only equally-weighted portfolio of all commodities generates a Sharpe ratio of 0.08 only. The Sharpe ratio of the S&P-GSCI over the same period merely stands at 0.19. Similar results are reported in Fernandez-Perez, Frijns, Fuertes and Miffre (2015), Fernandez-Perez, Fuertes and Miffre (2015) and Fuertes, Miffre and Fernandez-Perez (2015). In the same vein, Dewally, Ederington and Fernando (2013) use proprietary data on the positions of hedgers and speculators in the crude oil, gasoline and heating oil futures markets; they show that speculators (hedgers) make profits (losses) that are statistically and economically significant and that taking positions that are opposite to those of hedgers (as hedge funds do) translates into substantial outperformance. Again this highlights that hedging pressure and performance are closely related.

While this evidence would lead one to conclude that differences in hedging pressure predict differences in mean excess returns, a few exceptions are important to note. Daskalaki, Kostakis and Skiadopoulos (2014), for example, find that backwardated contracts for which hedgers are net short merely earn an insignificant 2.31% higher average excess return than contangoed contracts for which hedgers are net long, suggesting therefore that the data fail to support the hedging pressure hypothesis of Cootner (1960). Likewise, the spread in mean returns between extreme hedging pressure commodities is found to equal an only-marginally-significant 5.58% excess return a year (*t*-statistic of 1.66) in Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014).[4]

4. Long-Short Trend-Following Strategies

In this section, I review the evidence on the performance of various commodity-based trend-following strategies. I also argue that the trend-following signals studied, while not as

[4] Difference in results between *e.g.* Basu and Miffre (2013) and Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014) could be due to difference in the numbers of commodity futures considered at the time of portfolio formation. The wider cross-section considered in the former case may make it easier to detect extreme performers. Alternative explanations include difference in the numbers of commodities included in the long-short portfolios, as well as difference in the measurement of the hedging pressure signals.

theoretically grounded as roll-yields or hedging pressure, present similarities with the signals emanating from the theories of storage and hedging pressure. This suggests that past performance could be yet another manifestation of backwardation and contango.

4.1 Cross-Sectional Momentum Strategies

Momentum is a bet that past performance is an useful guide to future returns. In a seminal paper, Jegadeesh and Titman (1993) show that short-term price continuation prevails in equity markets: equities with the highest average returns in the recent past (so-called winners) outperform equities with the worst past performance (so-called losers) for up to 12 months ahead. This strategy is typically referred to as cross-sectional momentum since it picks up portfolios with extreme past performers out of the cross-section of available stocks.

While undisputed, the momentum profits are not yet fully understood. Some relate them to time-variation in expected returns (Chordia and Shivakumar, 2002), transaction costs (Lesmond, Schill and Zhou, 2004) or liquidity risk (Sadka, 2006; Asness, Moskowitz and Pedersen, 2013). Yet, rational asset pricing theories also have many detractors (Fama and French, 1996; Nagel and Lewellen, 2006 to name only a few articles). Alternative explanations rely on behavioral models such as Barberis, Schleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) which attribute price trend and abnormal returns to a slow assimilation of information into prices and to the cognitive errors that investors make when pricing information.[5]

[5] Investors, for example, have been shown to suffer from conservatism bias, biased self-attribution, overconfidence and bounded rationality. These behavioral attributes lead to price continuation first, followed by mean-reversion (once deviations from equilibrium are recognized), allowing for medium-run momentum profits and long-run contrarian profits.

Attempts have also been made to implement cross-sectional momentum strategies in commodity futures markets (Pirrong, 2005; Erb and Harvey, 2006; Miffre and Rallis, 2007; Shen, Szakmary and Sharma, 2007, to cite only the earliest papers). The ranking period over which past performance is measured and the holding period of the long-short portfolios range from 1 to 12 months, with equal weights assigned to the portfolio constituents. Table 2, Panel A reviews the evidence. The table presents the percentiles that are included in the long-short portfolios, the samples and cross-sections considered in the articles, as well as their main conclusions regarding performance. On average the Sharpe ratio of the cross-sectional momentum strategy is of a magnitude of 0.5 and substantially exceeds the Sharpe ratio of a long-only equally-weighted portfolio of commodity futures (*e.g.*, -0.24 in Miffre and Rallis, 2007) or that of the S&P-GSCI (*e.g.*, 0.06 in Blitz and De Groot, 2014).

4.2 Alternative Trend-Following Strategies

While cross-sectional momentum is the trend-following strategy that is the most mainstream, alternative price continuation strategies have also been shown to work well in commodity futures markets. Table 2, Panel B reviews the literature.

One such strategy is called time-series momentum (Szakmary, Shen and Sharma, 2010; Moskowitz, Ooi and Pedersen, 2012, to cite only the earliest papers). The idea is then to focus on a commodity's past return, to buy it if its past performance is positive and to sell it if its past performance is negative, holding overlapping positions for up to 12 months. The time-series momentum portfolio is then a weighted portfolio of these individual long-short positions. While time-series and cross-sectional momentum strategies are related, regressions of the performance of the former on that of the latter yields a significant alpha of 6.84% a year (t-statistic of 4.43), suggesting that the two signals are somehow different (Moskowitz, Ooi and Pedersen, 2012). The Sharpe ratio of the commodity-based time-series momentum portfolios is remarkable: it stands at 0.52 on average in Szakmary, Shen and Sharma (2010) and equals 1.05 in Hurst, Ooi and Pedersen (2013).

Other trend-following strategies use signals based on moving average ratios and channels (Szakmary, Shen and Sharma, 2010). The moving average ratio strategy considers the ratio of a short-term moving average (*e.g.*, 1-2 months) to a long-term moving average (*e.g.*, 6-12 months); the strategy goes long if the ratio exceeds $1 + b$ where $b = \{0, 0.025, 0.05\}$, short if the ratio is less than $1 - b$ and neutral otherwise. The strategy is first applied to each of the commodities considered and a portfolio that equally-weights the long-neutral-short positions is then formed. The channel strategy proceeds likewise but uses as signal the latest end-of-month settlement price of a commodity. The strategy takes a long (short) position if the most recent price exceeds (is below) the maximum (minimum) end-of-month price obtained over the recent past and is neutral otherwise. Results presented in Szakmary, Shen and Sharma (2010) as summarized in Table 2, Panel B show that moving average ratio and channel trading strategies are highly profitable when applied to commodity futures contracts. A variant of the moving average ratio strategy, recently proposed in Narayan, Ahmed and Narayan (2015), uses as signal for asset allocation the difference in returns between short-term and long-term moving averages, taking each month long/short positions in the commodity with the highest/lowest difference. The performance of such strategy is also found to be quite remarkable.

Another profitable trend-following strategy follows from George and Hwang (2004) and is called 52-week high. As reported in Bianchi, Drew and Fan (2015), the idea here is to split the cross-section of commodities into terciles based on the nearness of the current price to its highest level over the past 52 weeks. The long-short portfolio then buys the top tercile, shorts the bottom tercile and holds the long-short positions for a month. As reported in Table 2, Panel B, the 52-week high strategy, when implemented in commodity futures markets, performs well.

Of note, however, are the conclusions of Marshall, Cahan and Cahan (2008) who test more than 7,800 trading rules (such as filter, moving average, support and resistance, channel breakouts). They conclude that these strategies when applied to 15 individual commodity futures markets are not profitable after accounting for data mining and reasonable transaction costs. Possibly the lack of out-of-sample outperformance in this specific case reflects the fact that the strategies are implemented on a commodity-by-commodity basis. To generate better risk-adjusted performance, one might need to first generate active returns per commodity (as in Marshall, Cahan and Cahan, 2008) and then form portfolios that allocate wealth to either the whole-cross section (Table 2, Panel B) or extreme performers (Table 2, Panel A).

4.3 Possible Rationales for the Observed Profits

The debate regarding the reasons behind the momentum profits in commodity futures markets is still on-going. Reasons have been brought forward in support of both a behavioral explanation and a rational pricing explanation. For example, Miffre and Rallis (2007), Shen, Szakmary and Sharma (2007) or Moskowitz, Ooi and Pedersen (2012) show that momentum profits eventually reverse if one holds the long-short portfolios long enough; namely, beyond a year after portfolio formation. This can be considered as a sign of initial under-reaction and subsequent mean-reversion (Jegadeesh and Titman, 2001), a result that is in support of the sentiment-based behavioral theories of Barberis, Schleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), and Hong and Stein (1999).

Alternatively, the rational pricing explanation relies on the notion that the momentum portfolio picks up commodities that are prone to perform well according to the theories of storage and hedging pressure. To put this differently, it is argued that the momentum signal works well because it selects implicitly the commodities that the theories of storage and hedging pressure would choose explicitly. For example, Miffre and Rallis (2007) show that winners tend to be in backwardation as they have higher roll-yields than losers, while losers, having lower roll-yields, tend to be contangoed. Likewise, because low/high inventories are slow to replenish/deplete, Gorton, Hayashi and Rouwenhorst (2012) show that momentum winners/losers tend to be commodities with low/high levels of standardized inventory and relatively high/low bases. Along the same line, Bianchi, Drew and Fan (2015) point towards some overlap between winners and backwardated commodities (or between losers and contangoed commodities) by showing that trend-following strategies load positively on long-short term structure and hedging pressure risk factors.[6]

This suggests that the theories of storage and hedging pressure could explain part of the momentum profits. This is what Moskowitz, Ooi, and Pedersen (2012), Basu and Miffre (2013), Dewally, Ederington and Fernando (2013), and Bianchi, Drew and Fan (2015) report. A large part of trend-following profits does relate to hedging pressure and/or roll-yields, suggesting that momentum may well be yet another manifestation of the fundamentals of backwardation and contango. Having said that, it is important to note that the excess returns of trend-following strategies are not fully spanned by the excess returns of long-short term structure and hedging pressure portfolios. Thus, trend-following might bring forward information regarding the pricing of commodity futures that is not fully revealed by roll-yields and hedging pressure.

[6] Reversing the argument, Koijen, Moskowitz, Pedersen and Vrugt (2015) show that their commodity-based carry (or term structure) portfolio loads positively on a long-short momentum portfolio, suggesting again some overlap between winners and backwardated commodities with positive roll-yields or between losers and contangoed commodities with negative roll-yields.

5. Alternative Profitable Long-Short Strategies

This section reviews alternative signals that have been shown to work well in commodity futures markets. These sorting criteria are based on risk, value, skewness, liquidity, or open interest. Sorting commodities into portfolios based on these criteria often produces significant dispersions in mean returns suggesting that these alternative approaches are somehow useful to price commodity futures and could be used to design practical investment solutions in commodity futures markets.

5.1 Risk-Sorted Portfolios

Various measures of risk have been used to sort commodities into portfolios. One such measure is beta. Frazzini and Pedersen (2014) develop a strategy called betting against beta (BAB) that takes advantage of margin constraints and leverage aversion by buying low-beta underpriced assets with higher expected returns and shorting high-beta overpriced assets with lower expected returns. When applied to commodities, the BAB strategy *i*) estimates betas relative to a commodity portfolio that equally-weights the risk of each commodity, *ii*) sorts commodities in low/high beta portfolios based on the median beta, *iii*) rank-weights the commodities so that commodities with extreme betas are assigned higher weights, *iv*) rebalances the portfolios monthly and *v*) sets each portfolio beta at 1 at the time of formation. While the BAB strategy performs well for most of the other assets considered, in commodity futures markets it fails to produce a significant alpha relative to the relevant proxy of the market portfolio (annualized alpha of 2.5%, *t*-statistic of 0.83). Likewise, the Sharpe ratio of the commodity-based BAB portfolio is relatively low at 0.11 and compares poorly to those obtained when applying the BAB strategy in equity, fixed income, credit and foreign exchange markets.

Aside from beta, total risk[7] has also been used as sorting signal in commodity futures markets (Gorton, Hayashi and Rouwenhorst, 2012; Szymanowska, De Roon, Nijman and Van Den Goorbergh, 2014). The conclusion is then that systematically sorting commodities into portfolios based on total risk is a source of outperformance.[8] For example, Gorton, Hayashi and Rouwenhorst (2012) note that the high volatility portfolio outperforms the low volatility portfolio by 5.41% a year (*t*-statistic of 3.64); the obtained long-short volatility-based portfolio earns a Sharpe ratio of 0.58 versus 0.38 for an equally-weighted long-only portfolio of all commodities. Likewise, Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014) conclude that the quartile made of commodities with the highest coefficients of variation outperforms the least volatile quartile by 8.13% a year (*t*-statistic of 2.37).

In addition to beta and total risk, idiosyncratic volatility has also been used as criterion for tactical asset allocation. Following the conclusions of Ang, Hodrick, Xing and Zhang (2009) that stocks with high past levels of idiosyncratic volatility present very low returns, Fernandez-Perez, Fuertes and Miffre (2015) measure the idiosyncratic volatility of each commodity as the standard deviation of the residuals from a given pricing model,[9] buy the quintile of commodities with the lowest idiosyncratic volatility, short the quintile with the

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[7] Various measures of total risk have been used such as *i*) the standard deviation of daily futures returns in a given month minus the sample volatility in Gorton, Hayashi and Rouwenhorst (2012) and *ii*) the coefficient of variation defined as the variance of daily futures returns over a period spanning 36 months divided by the corresponding mean in Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014).

[8] Gorton, Hayashi and Rouwenhorst (2012) attribute the outperformance of the volatility-sorted portfolios to differences in inventory levels, while Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014) relate it to their basis risk premium.

[9] Idiosyncratic volatility is measured relative to either one of two benchmarks. The first benchmark includes traditional risk factors such as the four factors of Carhart (1997), the excess returns on Barclays bond index and on the S&P-GSCI. The second set includes long-short commodity portfolios based on roll-yields, hedging pressure and past performance. So unlike the first set, it recognizes the fundamentals of backwardation and contango that are key to the pricing of commodity futures contracts.

highest idiosyncratic volatility and hold the long-short portfolio for 1 month, equally-weighting its constituents. When traditional risk factors are used to extract the idiosyncratic volatility signal, the long-short portfolios offer sizeable abnormal returns, earning an average Sharpe ratio at 0.38 which compares favorably to that of the S&P-GSCI (at 0.02). In a similar spirit, the low-volatility long-short portfolio of Blitz and De Groot (2014) yields a Sharpe ratio of 0.35 that is much higher than that of the S&P-GSCI (0.06).

5.2 Other Sorting Signals

Asness, Moskowitz and Pedersen (2013) supplement this long list of asset allocation criteria with "value", where value is deemed to measure the cheapness/dearness of an asset today relative to its long-run price. In the case of commodities, it is defined as the log of the average spot price from 4.5 to 5.5 years ago divided by today's spot price. Systematically sorting a cross-section of 27 commodity futures on value, buying the top tercile and selling the bottom tercile is a source of outperformance in commodity futures markets: the resulting long-short portfolio indeed generates a Sharpe ratio of 0.26 or an annualized alpha of 7.7% (*t*-statistic of 2.02) relative to an equally-weighted portfolio of commodities.

Aside from the sorting criteria mentioned thus far (roll-yield, past performance, hedgers' hedging pressure and coefficient of variation), Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014) also review a large range of other signals, such as liquidity, inflation beta, dollar beta and open interest.[10] They then test whether systematically sorting commodities into quartiles based on either one of these signals is a source of outperformance in commodity

[10] Liquidity is measured as the average over two months of the daily ratio of volume to absolute return (as in Amihud, Mendelson and Lauterbach, 1997). Inflation betas (Dollar betas) are measured using 60-month rolling regressions of monthly futures returns on shocks to inflation (changes in the U.S. dollar versus a basket of foreign currencies). Open interest is proxied by the total interest in a given market. The rationale for treating open interest as signal for asset allocation comes from Hong and Yogo (2012) who show that commodity open interests lead commodity futures returns.

futures markets. Aside from the signals previously cited, liquidity and inflation betas are also found to be sorting criteria that trigger significant dispersions in mean returns. For example, the least liquid commodities outperform the most liquid by 9.40% a year (*t*-statistic of 2.22). Likewise, the quartile of commodities with the highest sensitivities to inflation shocks earns 9.56% more a year than the quartile with the lowest inflation betas (*t*-statistic of 1.99).

Adding to this extensive list of signals, Fernandez-Perez, Frijns, Fuertes and Miffre (2015) treat skewness as a tool for tactical asset allocation. They show that systematically buying commodities with the most negative skewness and shorting commodities with the most positive skewness yield a Sharpe ratio of 0.78, which exceeds that of traditional long-only and long-short commodity portfolios. The low-minus-high skewness portfolio generates an alpha of 6.58% (*t*-statistic of 3.58) relative to a set of long-only and long-short commodity portfolios. This indicates that its performance is not merely a reflection of the fundamentals of backwardation and contango. If so, it possibly shows investors' preferences for positively-skewed assets and their aversion towards negatively-skewed assets (as in, for example, Barberis and Huang, 2008).

6. Improving on the Basic Signals

This section reviews a recent literature that highlights the added value that comes from modifying or combining the original signals. The results, summarized in Table 3, indicate that modifying the initial signals or trading on more than one signal is more profitable than exploiting the basic signals.

6.1 Curve Strategies

Traditionally, investors roll their positions from front-end contracts to second-nearest contracts as the maturity of front-end contracts approaches; and, likewise, many of the strategies reviewed thus far identify buy or sell signals based on these series of front- or second-nearest futures prices. Mouakhar and Roberge (2010) however propose to go one-step further. For each of the 10 commodities considered, they buy the contract along the curve with the highest roll-yield and sell the contract along the curve with the lowest roll-yield; they then form an equally-weighted portfolio of these long-short positions which happens to post an interesting Sharpe ratio at 0.68.

Along the same line, Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014) analyze the performance of strategies that are implemented on distant contracts. In the case of a term structure approach, the idea is to sort the universe of commodities based on front-end roll-yields and to hold, instead of front-end contracts, one-period futures contracts with distant maturities. As reported in Table 3, Panel A, the added performance is quite remarkable with Sharpe ratios that range from 0.48 for the front-end term structure strategy to 1.06 for a 3-period forward version thereof. Likewise, forward-versions of the coefficient of variation and inflation beta strategies are found to perform well. That conclusion however does not hold for the momentum or hedging pressure strategies for which trading distant contracts is found to be unprofitable.

Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014) also isolate a term premium in commodity futures prices by buying distant contracts holding them until they mature, while simultaneously rolling short positions in front-end contracts. Equally-weighting these long-short positions across commodities yields a portfolio whose annualized mean excess returns range from 0.73% (*t*-statistic of 3.01) to 2.77% (*t*-statistic of 3.21) depending on the maturity of the distant contracts. As detailed in Table 3, Panel A, the corresponding Sharpe ratios stand at 0.59 on average and exceed those obtained on front-end portfolios.

Following a somehow similar line of thinking, De Groot, Karstanje and Zhou (2014) propose a spin-off of the cross-sectional momentum approach. Instead of trading contracts located at the front-end of the forward curve, the authors propose for a given winner (loser) to buy (sell) the contract along the term structure that is the most backwardated (contangoed). The potential benefits come from enhanced returns (through higher roll-yields) and reduced volatility (through the trading of less risky distant contracts; Samuelson, 1965). They show that integrating information from the term structure into the standard momentum strategy is a source of enhanced performance even after accounting for the higher transaction costs incurred on these less-liquid distant contracts.

6.2 Multi-Sort Approaches

Another way to enhance performance consists of *combining* the original signals instead of treating them as stand-alone. Fuertes, Miffre and Rallis (2010), for example, pool together the momentum and term structure signals by buying out of the momentum winners only the contracts with the highest roll-yields and by selling out of the momentum losers only the contracts with the lowest roll-yields. As detailed in Table 3, Panel B, the average Sharpe ratio of the resulting double-sort portfolios substantially exceeds that of the traditional single-sort strategies. Building on this result, Fuertes, Miffre and Fernandez-Perez (2015) develop an asset allocation strategy based on a triple-sort that combines the term structure, momentum and idiosyncratic volatility signals. The strategy consists of systematically buying contracts deemed to appreciate in value (namely, contracts with the highest roll-yields, the best past performance and the lowest levels of idiosyncratic volatility) and selling contracts deemed to depreciate in value (namely, contracts with the lowest roll-yields, the worst past performance and the highest levels of idiosyncratic volatility). The Sharpe ratios obtained, presented in Table 3, Panel B, show an enhanced performance of the resulting triple-sort strategy compared to the single-sort approaches.

6.3 Modifications of the Original Signals

I end this review by focusing on strategies that enhance performance by *modifying* the original momentum and/or term structure signals. Refining the basic term structure signal, Kim and Kang (2014) use as long-short signal the change in a commodity's roll-yield, in place of the roll-yield itself, and note substantial outperformance relative to the classic term structure signal. As reported in Table 3, Panel C, the Sharpe ratio of the enhanced term structure strategy more than doubles that of the basic approach.

Finally, improving jointly upon the term structure and momentum approaches, Boons and Prado (2015) design a strategy that uses as signal for asset allocation "basis-momentum" (measured as the difference in the 12-month momentum signals obtained using the first and second-nearest contracts). The resulting long-short basis-momentum portfolio generates a Sharpe ratio that is higher than that obtained on the standard basis or momentum strategies. With an annualized alpha of at least 12.76% (*t*-stat of 5.09), the excess returns of the high-minus-low basis-momentum portfolio are not spanned by the commodity factor pricing models of Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014) and Bakshi, Gao and Rossi (2015), suggesting that basis-momentum contains information beyond that captured by standard long-only and long-short commodity portfolios.

7. Conclusions

Even though the notions of backwardation and contango date back to Keynes (1930), Kaldor (1939), Working (1949), Brennan (1958), and Cootner (1960), the debate surrounding the profitability of long-short strategies in commodity futures markets is still very much thriving today. The conclusion seems to be that commodity futures risk premia depend on considerations relating to inventory levels, roll-yields, hedging pressure and past performance. Evidence indeed suggest that trading on these fundamentals is a source of outperformance in commodity futures markets: backwardated contracts with high roll-yields, scarce supply, net short hedgers, net long speculators and good past performance outperform contangoed contracts with low roll-yields, abundant supply, net long hedgers, net short speculators and poor past performance. Aside from these now-standard signals, it is interesting to note also the significant spreads in futures returns generated by strategies based on total or idiosyncratic risk, value, skewness, liquidity or open interest, as well as the good performance obtained by combining or modifying the original momentum and term structure signals.

On balance, most of these long-short portfolios present higher Sharpe ratios than their long-only counterparts (be it an equally-weighted portfolio of all commodities or a commodity index such as the S&P-GSCI). Therefore making the simplifying assumption that commodity futures markets are backwardated only (as do traditional and enhanced beta index providers) might be suboptimal. Rather one should contemplate a long-short approach to commodity investing that is similar to the one followed by active alpha index providers, commodity trading advisors and managed futures hedge fund managers. Likewise, researchers interesting in pricing commodities shall contemplate pricing models such as those of Basu and Miffre (2013), Szymanowska, De Roon, Nijman, and Van Den Goorbergh (2014) and Bakshi, Gao et Rossi (2015) that explicitly acknowledge the long-short nature of commodity risk premia.

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Table 1: Literature pertaining to the theory of storage

Strategies and authors	Constituents	Base assets	Sample	Performance
Panel A: Strategy based on roll-yields				
Erb and Harvey (2006)	50% breakpoint	12	1982-2004	SR(TS) = 0.47, SR(EW) = 0.10, SR(S&P-GSCI) = 0.26
Gorton and Rouwenhorst (2006)	50% breakpoint	36	1959-2004	SR(TS) = 0.76, SR(EW) = 0.43
Fuertes, Miffre and Rallis (2010)	Top/bottom quintiles	37	1979-2007	Mean SR(TS) = 0.48, SR(EW) = 0.31
Gorton, Hayashi and Rouwenhorst (2012)	50% breakpoint	31	1971-2010	SR(TS) = 0.67, SR(EW) = 0.38
Basu and Miffre (2013)	Top/bottom 15%	27	1992-2011	Mean SR(TS) = 0.39, SR(EW) = 0.08
Yang (2013)	Extreme portfolios out of 7	31	1970-2008	SR(TS) = 0.35
Daskalaki, Kostakis and Skiadopoulos (2014)	Top/bottom 5 contracts	22	1989-2010	SR(TS) = 0.61
Blitz and De Groot (2014)	Top/bottom 30%	24	1979-2012	SR(TS) = 0.65, SR(S&P-GSCI) = 0.06
Kim and Kang (2014)	Based on sign of signal	20	1990-2012	SR(TS) = 0.54
Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014)	Top/bottom quartiles	21	1986-2010	SR(TS) = 0.48, SR(EW) = 0.06
Bakshi, Gao and Rossi (2015)	Top/bottom 5 contracts	29	1970-2011	SR(TS) = 0.73
Bhardwaj, Gorton and Rouwenhorst (2015)	50% breakpoint	36	1959-2014	SR(TS) = 0.73, SR(EW) = 0.39
Fernandez-Perez, Frijns, Fuertes and Miffre (2015)	Top/bottom quintiles	27	1987-2014	SR(TS) = 0.39, SR(EW) = -0.02
Fernandez-Perez, Fuertes and Miffre (2015)	Top/bottom quintiles	27	1989-2013	SR(TS) = 0.41, SR(S&P-GSCI) = 0.02
Fuertes, Miffre and Fernandez-Perez (2015)	Top/bottom quintiles	27	1985-2011	Mean SR(TS) = 0.35, SR(S&P-GSCI) = 0.14
Koijen, Moskowitz, Pedersen and Vrugt (2015)	Based on sign of signal	24	1980-2012	SR(TS) = 0.60, SR(EW) = 0.08
Panel B: Strategy based on inventory levels				
Gorton, Hayashi and Rouwenhorst (2012)	50% breakpoint	31	1971-2010	SR(TS) = 0.46, SR(EW) = 0.38

SR stands for Sharpe ratio measured as the ratio of annualized mean excess returns to annualized standard deviation. TS stands for term structure. EW is a long-only equally-weighted portfolio of commodity futures. While some studies focus on assets other than commodities, this table solely reports results pertaining to commodity futures markets.

Table 2: Literature pertaining to trend-following strategies

Strategies and authors	Constituents	Base assets	Sample	Performance
Panel A: Cross-sectional momentum (Mom)				
Pirrong (2005)	Top/bottom quintiles	52 *	1982-2003	α = 6.84% for best Mom
Erb and Harvey (2006)	Top/bottom 4 performers	12	1982-2004	SR(Mom) = 0.55
Miffre and Rallis (2007)	Top/bottom quintiles	31	1979-2004	Mean SR(Mom) = 0.50, SR(EW) = -0.24
Shen, Szakmary and Sharma (2007)	Top/bottom terciles	28	1959-2003	SR(Best Mom) = 0.90
Fuertes, Miffre and Rallis (2010)	Top/bottom quintiles	37	1979-2007	SR(Mom) = 0.51, SR(EW) = 0.31
Gorton, Hayashi and Rouwenhorst (2012)	50% breakpoint	31	1971-2010	SR(Mom) = 0.65, SR(EW) = 0.38
Asness, Moskowitz and Pedersen (2013)	Top/bottom terciles	27	1972-2011	SR(Mom) = 0.53
Basu and Miffre (2013)	Top/bottom 15%	27	1992-2011	Mean SR(Mom) = 0.15, SR(EW) = 0.08, SR(S&P-GSCI) = 0.19
Blitz and De Groot (2014)	Top/bottom 30%	24	1979-2012	SR(Mom) = 0.59, SR(S&P-GSCI) = 0.06
Clare, Seaton, Smith and Thomas (2014)	Top/bottom quartiles	28	1992-2011	Mean SR(Mom) = 0.30
Daskalaki, Kostakis and Skiadopoulos (2014)	Top/bottom 5 performers	22	1989-2010	SR(Mom) = 0.58
Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014)	Top/bottom quartiles	21	1986-2010	μ(TS) = 9.09%, t-stat = 2.02
Bakshi, Gao and Rossi (2015)	Top/bottom 5 performers	29	1970-2011	SR(Mom) = 0.61, more than twice the SR of S&P-GSCI or CRB
Fernandez-Perez, Frijns, Fuertes and Miffre (2015)	Top/bottom quintiles	27	1987-2014	SR(Mom) = 0.62, SR(EW) = -0.02
Fernandez-Perez, Fuertes and Miffre (2015)	Top/bottom quintiles	27	1989-2013	SR(Mom) = 0.51, SR(S&P-GSCI) = 0.02
Fuertes, Miffre and Fernandez-Perez (2015)	Top/bottom quintiles	27	1985-2011	Mean SR(Mom) = 0.38, SR(S&P-GSCI) = 0.14
Panel B: Alternative trend-following strategy				
Time-series momentum (TSMom)				
Szakmary, Shen and Sharma (2010)	All base assets	28	1959-2007	SR(TSMom) = 0.52 on average
Moskowitz, Ooi and Pedersen (2012)	All base assets	24	1965-2009	Statistically significant α for 23 out of 25 strategies
Baltas and Kosowski (2013)	All base assets	71 *	1974-2012	Mean SR(TSMom) = 0.98, SR(MSCI World) = 0.21
Hurst, Ooi and Pedersen (2013)	All base assets	24	1985-2012	SR(TSMom) = 1.05
Clare, Seaton, Smith and Thomas (2014)	All base assets	28	1992-2011	Mean SR(TSMom) = 0.58
Moving average ratio (MAR)				
Szakmary, Shen and Sharma (2010)	All base assets	28	1959-2007	Mean SR(MAR) = 0.72
Narayan, Ahmed and Narayan (2015)	Top/bottom 1 performer	19	1983-2012	μ(MAR) = 10.3%
Channel				
Szakmary, Shen and Sharma (2010)	All base assets	28	1959-2007	Mean SR(Channel) = 0.82
52-week high				
Bianchi, Drew and Fan (2015)	Top/bottom terciles	30	1977-2013	SR(52-week) = 0.67, SR(Mom) = 0.57

SR stands for Sharpe ratio measured as the ratio of annualized mean excess returns to annualized standard deviation. μ stands for annualized mean excess returns. EW is a long-only equally-weighted portfolio of commodity futures. * notifies that the base assets include both commodity and financial futures. Only results pertaining to ranking and holding periods that range between 1 and 12 months are summarized here.

Table 3: Literature that improves upon the basic signals

Strategies and authors	Base assets	Sample	Original signals / Original strategies		Improved signals / Improved strategies	
			Strategy	Average SR	Strategy	Average SR
Panel A: Curve strategies						
Mouakhar and Roberge (2010)	10	1994-2006			Long-short curve	0.68
De Groot, Karstanje and Zhou (2014)	27	1990-2011	Front-end momentum	0.73	Curve momentum	0.96
Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014)	21	1986-2010	Front-end TS	0.48	2-period forward TS	0.88
					3-period forward TS	1.06
					4-period forward TS	0.90
Szymanowska, De Roon, Nijman and Van Den Goorbergh (2014)	21	1986-2010	Front-end EW	0.06	Long second nearest, Short front	0.61
			Front-end TS	0.48	Long third nearest, Short front	0.52
					Long forth nearest, Short front	0.64
Panel B: Multi-sort approaches						
Fuertes, Miffre and Rallis (2010)	37	1979-2007	Momentum	0.61	Double-sort	0.78
			TS	0.59		
Fuertes, Miffre and Fernandez-Perez (2015)	27	1985-2011	Momentum	0.37	Triple-sort	0.69
			TS	0.34		
			Idiosyncratic volatility	0.38		
Panel C: Modification of the original signals						
Kim and Kang (2014)	20	1990-2012	TS	0.54	Change in roll-yield	1.33
Boons and Prado (2015)	21	1959-2014	Momentum	0.63	Basis momentum	0.90
			TS	0.53		

SR stands for Sharpe ratio measured as the ratio of annualized mean excess returns to annualized standard deviation. TS stands for the term structure strategy based on roll-yields.