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Skewness Based Investment Strategies on Commodity Futures

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Abstract:

Mitton & Vorkink (2007) and Barberis & Huang (2008) have shown that investors exhibit lottery (or skewness) preferences where they prefer assets that have small probabilities of delivering large payoffs. Skewness preferences have also been shown to manifest in commodity futures through selective hedging (Stulz 1996). Selective hedging stands for a practice, where subjective views are incorporated into hedging decisions to maintain exposure to upside events. As such hedgers in commodity markets sell more futures (less) futures when the futures returns are negatively (positively) skewed (Gilbert, Jones & Morris 2006). Subsequently, positively skewed futures are expected to become overpriced and negatively skewed futures underpriced (Fernandez-Perez, Frijns, Fuertes & Miffre 2018). The performance of alternative skewness based strategies on commodity futures are analyzed in this thesis.

The commodity futures risk premium has recently been decomposed into a spot premium and a term premium by Szymanowska, Roon, Nijman & Goodberg (2014). The spot premium represents the near-term price risk of the underlying asset and is captured by either long or short positions in the front contract. The term premium is interpreted as deviations from expectations hypothesis, where markets might for example expect changes in convenience yields. The term premium can be captured by calendar spreads, where a short position is taken on the front contract and a long position is taken on a farther maturity contract.

Following Fernandez-Perez et al (2018) a skewness strategy that captures spot premia is implemented. The spot strategy ranks commodities into quintiles by realized daily return skewness over the previous year and buys front contracts on the lowest quintile and shorts front contracts on the highest quintile. In addition, novel term premia strategies are also implemented. The term premia strategies use the same ranking instrument as the spot strategy and the first term based strategy buys calendar spreads on commodities with below-median skewness and the other strategy buys spreads on commodities with above-median skewness. The term premia strategy is implemented in alternative maturity series, where the farther contract matures in at least 4, 6, or 8 months. The data contains 25 commodities that are traded in the US and the period ranges from 03/1996 – 10/2019. Data is obtained from Datastream.

The spot skewness strategy delivers a significant average excess return (13,2% pa) and significant alpha (9,8-12% pa) when regressed on commodity pricing models. The results of the spot skewness strategy are driven by the poor performance of the short leg, positively skewed commodities, and support the theories of lottery preferences and selective hedging. The term premia skewness strategies deliver smaller but significant average excess returns. However, the risk-adjusted returns are found to be insignificant when term-structure based factors are controlled for. As such, the skewness signal does not contain novel information about term premia.

KEYWORDS: Commodity futures, skewness, lottery preferences, spot premia, term premia

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1 INTRODUCTION

One of the main tenets of finance is that higher risk should be rewarded by higher returns. One measure of risk is the skewness of assets returns. Positive skewness implies a higher probability of larger profits and negative skewness implies a higher probability of larger negative returns or crash risk. Thus, investors require a premium for holding assets that exhibit negative return skewness (Kraus & Litzenberger 1976, Harvey & Siddique 2000, Jondeau, Zhang & Zhu 2019). Another complementary strand of literature argues that investors have lottery preferences and they tend to concentrate on assets that have positively skewed returns. As a result, positively skewed assets become overpriced and their expected returns decrease. (Mitton & Vorkink 2007, Barberis & Huang 2008).

The skewness preferences can manifest themselves in commodity futures as well through selective hedging (Stulz 1996). In selective hedging subjective views of the risk manager affect the hedge ratio employed and the goal is usually to preserve exposure to beneficial events such as positively skewed returns for long positions. Gilbert, Jones & Morris (2006) show that given positive skewness preferences, hedgers will sell more (less) futures on negatively (positively) skewed assets. Therefore, Fernandez-Perez, Frijns, Fuertes & Miffre (2018) argue that realized daily return skewness might be able to predict future excess returns on commodity futures.

Understanding factors that influence expected returns in commodity futures is timely as long-only index investing has delivered poor returns in the recently (Erb & Harvey 2016, Blocher, Cooper & Molyboga 2018). Commodities are procyclical, or very strongly tied to the current economic environment, and the recent poor performance by commodity indices is likely due to lack of inflation (Levine, Ooi, Richardson & Sasseville 2018). In addition, adjusting commodity supply is a lengthy process and subsequently, commodities futures tend to experience long trends of increasing or decreasing prices (Fabozzi, Füss & Kaiser 2008: 3-4). Furthermore, the diversification benefits have declined following the financialization of commodities and commodity volatility tends to comove with equity volatility (Tang & Xiong 2012, Christoffersen, Lunde & Olesen 2018).

Financial literature proposes tactical or active strategies, that account for the commodity futures term-structure, to overcome the poor recent results of passive long-only investing. These strategies, such as momentum or carry have been shown to deliver significant and positive average returns that are not correlated with the performance of equity markets (Erb & Harvey 2006, 2016, Fuertes, Miffre & Fernandez-Perez 2015). Strategies based on the skewness of commodity futures could offer a desirable alternative for investors.

While the results are sometimes contradictory, numerous studies provide evidence that the relations between skewness and returns are negative in various asset classes such as stocks (among others, Amaya, Christoffersen, Peter & Vasquez 2015) and commodities (Fernandez-Perez, Frijns, Fuertes & Miffre 2018 among others). In this thesis, the interest is in testing the performance of a skewness-based strategy on commodity futures as in Fernandez-Perez et al (2018) and alternative implementations that aim to capture term-premia.

1.1 Purpose of the Thesis

The purpose of the thesis is to study the performance of the skewness strategy of Fernandez-Perez et al (2018) on a similar sample of commodity futures. The strategy buys commodities that have the lowest skewness based on daily returns on the previous year and sells commodity futures that have the highest skewness. A recent study by Szymanowska, de Roon, Nijman & van den Goodbergh (2014) showed that commodity return can be divided in to spot premia, price risk in the underlying asset, and term premia, risks related to changes that affect the slope of the futures curve. The first test is to study whether the skewness strategy of Fernandez-Perez et al (2018) delivers significant average spot premia. Additionally, the skewness signal’s ability to generate term premia is investigated, where commodities are ranked into Low and High skew portfolios using the periods' median as the cutoff point. Low and High skew buy calendar spreads with three different more distant maturities, where a long position in the more distant contract and short position in the front contract are taken. Following the strong performance reported by Fernandez-Perez et al (2018) the first hypothesis is:

H1: Long-short skewness portfolio yields significant and positive average spot premia.
H2: Low skew and high skew portfolios yield significant and positive average term premia.

The second purpose is to examine whether the skewness strategies yield significant alpha (abnormal or risk-adjusted return). The literature has proposed distinct factors that have been shown to capture spot and term premia (Bakshi, Gao & Rossi 2017, Szymanowska et al 2014, Blocher, Cooper & Molyboga 2018). The idea is to test whether the skewness factor delivers returns that are not related to other well-performing risk-factors or active strategies. Following Fernandez-Perez et al (2018), the first model is proposed by Bakshi, Gao & Rossi (2019) and presents factors that capture the spot premia,. The factors are an equally-weighted long-only portfolio, carry portfolio that buys backwardated commodities and sells contangoed commodities, and a momentum portfolio that buys recent winners and sells recent losers. Thus, the third hypothesis is the following :

H3: The long-short skewness portfolio delivers significant time-series alpha (risk-adjusted spot returns) when regressed on the three factors of Bakshi, Gao & Rossi (2017) 3-factor model.

Szymanowska et al (2014) and Blocher et al (2018) show that portfolios that are sorted on commodity futures basis, the ratio of the second nearest futures price to the front futures price, capture term-premia and span term-premia of other sorting instruments such as momentum. The Lterm portfolio buys calendar spreads on commodities that have below-median basis (measured at the front of the futures curve) and Hterm buys calendar spreads on commodities that have above-median basis. These factors shall be used in an asset pricing test on the term-premia of the skewness sorted portfolios and the final hypothesis is:

H4: Low skew and high skew deliver significant time-series alpha (risk-adjusted term-premia)

1.2 Structure of the Thesis

This study is constructed as follows. Section two presents an overview of commodity futures markets, historical return, risk and diversification benefits and how these seem to change over time as well as hedging. Section three reviews commodity futures pricing models and summarizes the theories that predict commodity futures risk premia. Section four examines the lottery theories for skewness preference and covers the reasons why lottery-like assets are expected to underperform. In addition, the literature review is presented in section 4, where the results of previous studies that investigated the relation between skewness and expected returns are examined. Section five goes over the data and methodology applied in this thesis. Section six presents empirical results and discussion. Section eight concludes.

2 COMMODITY FUTURES MARKETS

A futures contract is a derivative contract, meaning that its profit and value depend on the performance of the underlying asset. A future is a binding contract where the buyer (long position) agrees to buy the asset from the seller (short position) at the price agreed upon when entering the contract. A futures contract is similar to a forward contract, however, the former are standardized contracts traded exchanges and settled daily. Forward contracts are traded over-the-counter, are tailored by those entering the contract and usually settled at maturity. (Fabozzi et al. 2008: 15-18.)

This section provides outlines the distinct characteristics of commodities, futures markets and market participants. The return calculation for commodity futures is also examined since as finite maturity derivate contracts they differ from traditional assets such as stocks. The risk characteristics and diversification benefits are also examined as they are commonly offered as motivation for investing in commodities (Gorton & Rouwenhorst 2006). Finally hedging and its implementation are covered, as commodity futures were initially developed as a way to hedge (transfer) risks.

2.1 Overview of Commodity Futures Trading

Commodities are a unique asset class, that differs from others in three ways. First commodities are real assets often used for consumption or production, not investment. Therefore, commodities provide utility and are not primarily held as capital assets or as a store of value (precious metals are an exception). Furthermore, the supply of commodities is limited. For instance, increasing mining of precious metals is costly and takes time and agricultural commodities have limited yearly harvests and experience strong seasonality. On the second point, commodities are heterogeneous, with each commodity having specific properties. Consequently, commodities are often classified into different sectors such as hard and soft commodities. Hard commodities refer to products related to energy, precious or industrial metal sectors. Softs contain weather-dependent, perishable commodities often used for consumption from the agricultural sector. Finally, storability differs greatly among commodities and subsequently affects futures pricing. Commodities that have a high degree of storability are not perishable and as such the costs of storage remain low. Difficult to store commodities, on the other hand, have a limited life-cycle, for instance, livestock needs to be fed and housed at costs. Related to storage costs is the availability of commodities as supply adjusts slowly. Thus, commodities can experience shortages and physical ownership can act as insurance to these risks. (Fabozzi et al. 2008: 6-7.)

Futures contracts are exchange-traded standardized contracts. The exchange, such as Chicago Mercantile Exchange (CME) or Intercontinental Exchange (ICE) sets the contract specifications which usually include quality of the underlying, contract size, price determination, trading hours, tick (smallest price fluctuation), currency, daily price limit, last trading day and regulations for delivery. Commodity futures can be settled at maturity either by delivery, which happens rarely or by closing out the position. Closing out is done by entering the opposing side of the original position which brings the net position at the exchange to zero. Investors are required to deposit initial margin at the broker for each futures contract. The margins posted mitigate credit risk. Futures contracts are settled daily, where gains or losses are allocated to the margin accounts. The investors are required to uphold a maintenance margin, which is the minimum deposit required by the exchange per contract. The broker issues a margin call, should the investors' deposit fall below the maintenance margin, and the investor must post additional capital to meet the initial margin or the position will be closed at a loss. The margin deposits receive money market interest rates and investors are usually able to withdraw funds that exceed the initial margin. The initial margin is usually a small fraction of the total value of the commitment, making commodity futures levered investments. (Fabozzi et al. 2008: 15-18, Hull 2015: 24-31.)

Futures market participants are classified into hedgers, speculators and arbitrageurs, in accordance for their trading motivations. Hedgers usually consist of producers, or manufacturers (consumers), who are exposed to the price risk of the underlying commodity and use commodity futures to transfer risks or as insurance. For instance, producers are net long in the underlying commodity, where they benefit from price increases as this means their sale price also increases. Alternatively, producers' profits suffer from price decreases. Producers can set up a short hedge by selling a commodity future, which effectively locks the price of the sale transaction in the future. The opposite holds for consumers, who are net short in the underlying and can use long futures positions to eliminate losses that would occur from price increases. (Fabozzi et al 2008: 5)

Speculators trade commodity futures purely for profit or diversification benefits. Where hedgers seek to eliminate price risk, speculators take on price risk by placing deliberate bets on whether the future's prices increase or decrease. Since futures are levered instruments and speculators do not hold offsetting cash positions, speculation in commodity futures can deliver large gains or losses. Traditionally, speculators are also seen as liquidity providers who balance the long and short hedges. (Fabozzi et al 2008: 7). However, recent studies have shown that liquidity provision can flow from hedgers to speculators as speculators need to constantly rebalance for trend-following strategies or deleverage investments during market-wide financial turmoil (Cheng, Kirilenko, Xiong 2015; Gorton, Rouwenhorst, Tang 2020).

Arbitrageurs also trade for profit, but unlike speculators, they do not take risks. Arbitrage stands for obtaining riskless profit by exploiting market frictions, where prices are not instantly adjusted across spot (cash) and futures markets. Arbitrageurs use time and location induced price differences to trade and, subsequently eliminate price differences. Due to the degree of difficulty and information intensiveness, arbitrageurs are the smallest market participant group, since it requires a lot of recourses and market-specific knowledge. (Fabozzi et al 2008: 7)

2.2 Commodity Futures Return

When a futures contract is entered the buyer (long position) agrees to buy the asset at the price agreed upon at maturity. The seller of the futures contract (short position) agrees to sell the asset at the same conditions. For forward contracts, the payoff in the long position is the price of the underlying at maturity less the settlement price and the opposite holds for the individual on the short position. No upfront investment is necessary for forward contracts so the payoff equals the return. When trading futures investors are required to post collateral, however since this collateral is returned at maturity (plus or minus the margin depending on price development) futures can be thought of a no-cost investment as well. For a single futures contract, the payoff is similar to a forward contract and the payoff for both long and short positions are plotted on figure 1. (Hull 2015: 5-8; Gorton & Rouwenhorst 2006)

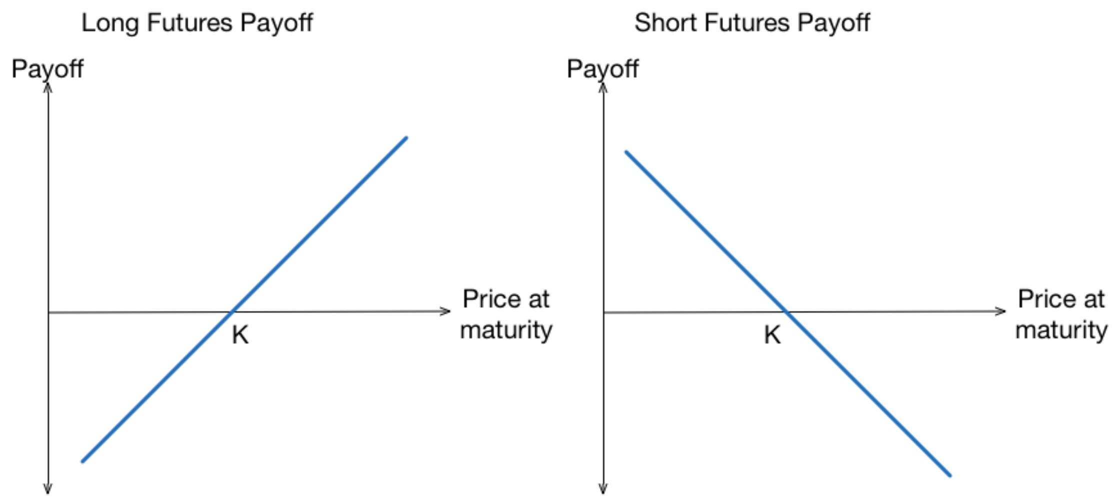


Figure 1: Payoff for a single forward and futures contract

In practice, investors need to roll from one futures contract to another to maintain exposure, due to the limited maturity of individual futures contracts. In addition, investors usually earn interest on the collateral posted, which needs to be taken into consideration for a total futures return. The total return for a futures position is given by (Fabozzi et al 2008:27, Bessenbinder 2018b):

$$\text{Total futures return} = \text{Price return} + \text{Roll return} + \text{Collateral Return} \quad (1)$$

The price or spot return reflects changes in the settlement price of the futures contract in question as time advances. The front futures price is commonly used as the spot price in the literature as actual physical spot markets tend to be illiquid in comparison to the front-end futures. Front futures are the futures contract nearest to expiry and the position is rolled to the second nearest usually before the maturity month. The spot return reflects changes in supply and demand for the future in the near term. For instance, a long position incurs a profit if the demand for the front-end futures increases driving the settlement price up. (Fabozzi et al 2008: 23-24)

The roll return is a product of the futures-term structure, the price of the front-end contract converges with the spot price and the second-nearest futures settlement price reflects the market's expectation of spot price in the future. Rolling over futures contracts are done by closing out the initial position and entering the same position on the second nearest futures contract. The roll return is the difference between the second-nearest futures’ price and the front futures’ price at the roll date. For instance, long-positions tend to experience profits when the term-structure is downward slopping (backwardation). (Fabozzi et al 2008: 24.) However, it should be noted that roll return is not an actual cash flow since one contract is bought and a different one is sold. Rather, roll return is an accounting entity that adjusts profits of a futures exposure to the gains or losses from exciting the previous contracts ie rolling the position (Bessenbinder 2018b).

Investors are also required to post collateral for the initial margin when entering a futures position. Therefore, part of the futures return is attributable to the interest earned on the collateral. In the literature fully cash collateralized positions are usually assumed, meaning that an amount equal to the underlying futures position is allocated to cash, which earns a risk-free interest rate. For a portfolio or an index consisting of commodity futures the total return is given by (Fabozi et al. 2008 23, 25):

$$\text{Total portfolio return} = \text{Spot return} + \text{Roll return} + \text{Collateral return} + \text{Rebalancing return} \tag{2}$$

The rebalancing (or diversification) return stems from the fact that commodities included in portfolios or indexes tend to have very little correlation among each other. Furthermore, as strategies are often rebalanced monthly, the act of doing so resembles a smart beta strategy. While exact results depend on the rebalancing scheme (equal or value-weighted, production-weighted), the act of rebalancing can for instance reduce the weight of recent winners and increases the weight of recent losers, effectively lowering the standard deviation and while still yielding returns that potentially match passive buy-and-hold. (Erb & Harvey 2006, Erb & Harvey 2016.)

In this thesis, monthly and daily returns on commodity portfolios are reported in the excess return form, less the risk-free interest, following the literature (among others Fernandez-Perez et al 2018). Put differently a fully collateralized position is assumed, where half of the trading capital is allocated to risk-free bonds and a half to the futures strategies. Collateral returns are excluded from the excess return calculations. Fuertes, Miffe & Rallis (2010) note that the strengths of the procedure are that no liquidations take place as liquid assets are available and the unlevered position is not exposed to liquidity risk. Furthermore, the excess return is a conservative estimate of what the strategies would yield in the real world as collateral returns are not considered. Thus, the excess return is given by (Fabozzi 2008: 27)

$$\text{Excess return} = \text{Price return} + \text{Roll return} \tag{3}$$

Whether commodity futures exhibit a risk premium, for passive or active investors, has been controversial. Gorton & Rouwenhorst (2006) study the performance of an equally weighted and monthly rebalanced portfolio that goes long on the front contract of 36 commodities. The authors find that their equally weighted portfolio yields equity-like returns during the years 1967-2004 and is not correlated with the equity markets. Erb & Harvey (2006) question these findings and argue that the return is due to rebalancing profits and the strategy might not be obtainable for standard investors due to liquidity issues. Furthermore, the authors point out that of the 36 commodities only 1 has statistically significant positive profits, meaning that long-only investing might not be advisable in commodity markets. Finally, Erb & Harvey (2006) discover that momentum and carry strategies work well in commodity markets and advocate the use of tactical or active strategies instead of passive ones.

Erb & Harvey (2016) revisit the question of whether active (tactical) or passive strategies are warranted following the poor performance of the S&P GSCI commodity index after the financial crises. The authors show that historically roll returns explain much of the variation in commodity futures return and similarly income return (roll return + collateral return) is positively related to inflation. Thus, long-only buy-and-hold strategies, such as those that invest in the S&P GSCI index, focus only on price appreciation that may deliver poor returns in the long run as they miss important drives of futures return.

Ilmanen (2011: 219-226) provides an anecdotal example of the importance of roll returns. The author points out that a price return in light crude oil for the front contract was effectively zero, ie price roughly 90$ per barrel at both dates if an investor entered into a front contract crude oil index in 2007 and excited in 2009. The actual return however was roughly -30% largely due to negative roll returns from contango (futures prices increase for longer contracts and tend to decrease nearing maturity), which were incurred as the index was forced to roll from one contract to another at poor prices. Put differently maturing contracts were sold at a price less than bought, and the second nearest contracts were bought at high prices.

Fuertes, Miffre & Fernandez-Perez (2015) provide further evidence that tactical strategies, that are actively managed, consider backwardation/contango characteristics and include short positions accordingly, deliver better returns relative to index investing in commodity markets. The authors show that strategies, that form long-short portfolios according to momentum, term-structure (carry) and idiosyncratic volatility deliver better returns and Sharpe-ratios relative to the SP GSCI, well known long-only commodity benchmark index. Furthermore, a triple-screen strategy that corporates information from all the active strategies further enhances outperformance and is less correlated with equity markets than the S&P GSCI. Therefore, the authors argue that commodity investing should be based on theories that predict risk premiums or explain backwardation and contango characteristics, which may lead to both long or short positions, rather than take a passive long-only approach.

Levine, Ooi, Richardson & Sasseville (2018) examine the performance of passive long-only positions on front commodity futures for a long sample spanning back to 1877. The authors find that in addition to commodity term-structure (backwardation/contango) the different economic states have a large impact on the performance of commodities. Specifically, commodity returns are found to be higher in periods with positive inflation shocks and expansionary economic states, regardless of the term-structure. The authors find that during their long sample commodities delivered significant average returns. However, the researchers note that due to the procyclical nature of commodities and positive correlation with inflation, commodities can also suffer from long periods from poor performance during low inflation or market downturns. The researchers conclude that commodities are a valuable investment for investors as Sharpe ratios tend to improve over 60/40 stock portfolios when commodities are added.

2.3 Commodity Futures Risk and Diversification Benefits

Traditionally investments in commodity futures have been considered great for risk reduction due to their diversification benefits and decent risk-return characteristics. Erb & Harvey (2006) document that over a period from 1982 – 2004 commodities had very low correlations amongst each other. Gorton & Rouwenhorst (2006) find that an equally-weighted and monthly rebalanced portfolio of commodities was uncorrelated with US equities, had a negative correlation with US Bonds, with a similar risk-return profile from 1959-2004. Bessembinder (1992) and Roon, Nijman and Veld (2000) show that systemic risk, proxied by equity market returns, does not explain commodity futures returns, while idiosyncratic risk conditional on hedgers hedging demand does. Finally, Kat &

Oomen (2007) find that the average annualized volatility of commodities was 27,8% which did not greatly differ from that of the average large-cap US stock 29,5%.

Tang & Xiong (2012) find that the diversification benefits of commodity futures have declined since the early 2000s due to the financialization of commodities. The financialization of commodities refers to a phenomenon experienced in the mid-2000s, where a large amount of capital was allocated to commodity futures markets by financial investors such as hedge funds and commodity index traders (CITs), increasing the amount of commodity index instrument purchases from 15 billion USD in 2003 to 200 billion USD by 2008. The capital inflow coincided with a boom and bust cycle in commodities, where the price and volatilities peaked during 2008 and subsequently crashed. Furthermore, the correlations between commodities among themselves and with other asset classes increased, peaking during the financial crises of 2008.

Tang & Xiong (2012) argue that the effects observed during the late 2000s are largely driven by the financialization effect and less by changes in demand by the real economy. The authors maintain that financial commodity index investors (CITs) focus on strategic portfolio allocation across asset classes and tend to move in and out of commodity indices at the same time. Based on the argument, commodities that are included in indices should have larger capital inflows and correlations with each other and alternative assets, since index investors deleverage commodity positions in tandem, due to negative developments in other asset classes. The researchers find supportive evidence for the hypothesis as the correlations of commodities within popular indices (S&P GSCI, DJ UBSCI) increased more relative to non-index commodities in the period leading to the financial crises and stayed at an elevated level. Furthermore, the fundamental demand is only partly attributable to the increased correlations across commodities and other assets, as emerging markets returns have a similar impact on the correlation growth of both index and non-index commodities. Finally, the emerging market growth stagnated in 2006 while correlations continued to climb among index commodities, pointing toward the financialization effect.

Cheng, Kirilenko & Xiong (2015) find further evidence of the price impact caused by financial investors, mainly hedge funds and CITs during the financial crises. Financial investors might be forced to liquidate commodity futures positions due to lower risk appetite, binding funding and risk constraints, especially during crises. The authors use changes in the VIX index as a proxy for financial shocks and find a negative relation between the weekly positions of financial investors and changes with both contemporaneous and lagged changes of the VIX. The evidence is in line with the time-varying risk-bearing capacity of financial investors as they unwind their commodity futures positions following shocks. The position changes were met by commercial hedgers, who contrary to the risk-sharing view of commodities, ended up holding more risk. The authors conclude the traders that drive the price are the ones with the strongest incentive to trade. Contrary to the hedging pressure theory (Hirshleifer 1988) price changes can also be driven by liquidity needs of financial investors, whose trading motivations are driven by events in other asset classes.

Christoffersen, Lunde & Olesen (2019) study high-frequency intraday data and find that the average return correlations between US equity markets and 15 commodities peaked during the financial crises but have subsequently fallen to the pre-crisis levels. Similarly, volatilities of individual commodities have not trended up and neither has the degree of market integration during the years 2004 – 2015. However, volatility correlations across commodities and other assets increased substantially and remained at a high level at the end of the period. The first principal component of commodity volatilities captures on average 55% of the variation, relative to 24% for returns, and is found to be strongly and positively related to the level of volatility in US equity and bond markets especially during recessions. Put differently, commodity volatilities tend to increase as volatility in equity and bond markets increases. Finally, the authors estimate stock market betas for commodities, sensitivities to stock market return, and find that the betas and their explanatory power increased considerably during the financial crises for energy and precious metals, less so for agriculture and lives stock. The researchers conclude that commodities diversify equity market exposure well during normal times, but the diversification benefits decrease substantially during volatile times.

2.4 Hedging with Commodity Futures

One of the primary classes of entities in the futures market is hedgers. Hedgers refer to either producers of the commodities or manufacturers who need the commodities as input for their products or services. Futures market initially developed as producers (short hedgers) or manufacturers (long hedgers) needed a way to limit their exposure to adverse price movements and transfer risks associated with these. The arguments for hedging builds on the fact that using futures a company can reduce the volatility of earnings when buying or selling commodities. Thus, the hedgers face less uncertainty and can focus on other areas for which they have a comparative advantage. Similarly, hedging companies usually have large transactions and costs of hedging per transaction tend to be lower. (Hull 2015: 49-53)

On reasons against hedging, firstly, investors in the company can reduce their risks by diversifying their investments, reducing their exposures and rendering the companies hedging practices unnecessary. Furthermore, if the company operates in an industry where competitors do not hedge, the act of hedging might increase uncertainty. This follows from the competitive pressures, where price uncertainty usually leads to adjustments on other costs leaving the profit margins of non-hedging companies roughly constant. Finally, hedging only limits the range of possible outcomes, both good and bad. Put differently if the prices of the asset increase, a short hedger will occur a loss as it is forced to sell the underlying at the lower agreed-upon price. (Hull 2015: 49-53)

Another issue related to hedging is that in practice perfect hedges are rarely achievable. Difficulties arise when, for instance, the asset which is to be hedged does not have liquid contracts and thus the futures contract chosen might have a different underlying asset. Another possible issue is that the exact time, when the asset is to be sold or bought is not known. Furthermore, the hedge might require that the positions are closed out before the delivery month. These issues give rise to basis risk defined as:

$$\text{Basis risk} = \text{Spot price hedged asset - Futures price of contract used} \quad (4)$$

Basis risk arises as the prices at maturity are not known in advance. Since either the maturity of the contract or the underlying asset does not match with the hedging needs the position is closed ahead of maturity. Thus the profit or loss realized in the futures position is unknown as is the spot price of the asset in the future. (Hull 2015: 54-55)

In the mean-variance framework, the optimal contract and the number of contracts needed are the ones that reduce the variance (or volatility) as much as possible. Since the maturity and the underlying rarely match in practice setting a hedge ratio equal to 1 is not optimal. Hedge ration being the fraction of exposure and size of the underlying futures position. The minimum variance hedge ratio is calculated as (Hull 2015: 59):

$$h^* = \rho * \frac{\sigma_S}{\sigma_F} \quad (5)$$

Where:

h^* = Minimum variance hedge ratio

ρ = Correlation coefficient between changes in spot price and changes in the futures price

σ_S = Standard deviation of spot price changes

σ_F = Standard deviation of futures price changes

Then the optimal number of contracts can be calculated as (Hull 2015: 60):

$$N^* = \frac{h^* Q_A}{Q_F} \quad (6)$$

Where:

N^* = Number of contracts needed

Q_A = Size of the position to be hedged (in units)

Q_F = Size of the position in the futures contract (in units)

3 COMMODITIES FUTURES PRICING

Modern financial theory suggests that excess returns of assets are compensation for the systematic component of price movements. Put differently un-diversifiable risks or factors are the main drivers of the prices of assets. However, commodities are primarily physical consumption assets, not investment assets, and are therefore traditional factors tend to fail in pricing commodities as they behave differently. The issue is exacerbated by the heterogeneous structure of commodities. As such numerous theories and commodity-specific models have been developed to price commodities, explain and predict their risk premiums for the commodity market as a whole and individual commodities (Daskalaki, Kostakis & Skiadopoulos 2014; Rouwenhorst & Tang 2012).

This section firstly goes over theories that predict risk premiums and their main drivers. Second, the traditional cost-of-carry pricing model is examined, as to highlight how futures prices are set in theory. Commodity futures risk premia can also be decomposed to a part that is due to changes in underlying prices (spot premia) and another part due to changes in expectations regarding the commodity basis (term premia). Ways to capture these different premia are outlined. Finally, recent factor-based commodity pricing models are examined, as they provide valuable insight into the behavior of commodity returns and are need to be controlled for when examined the skewness based strategies.

3.1 Commodity Futures Risk Premium Theories and Evidence

The first theories that predict a commodity risk premium are based on the insurance principle. The theory of normal backwardation proposed by Keynes (1923), Hicks (1939) posits that mainly producers, or holders of inventory, use commodity futures for hedging and sell futures contracts to lock in the price of inventory. The hedgers (producers) use commodity futures to eliminate price risk and are required to set the futures price below the expected spot price to encourage speculators to bear the price risk associated with uncertain future spot prices. Thus commodity futures are expected to lie more often in backwardation, where the term structure of futures prices is downward slopping and futures prices are expected to rise when nearing maturity. As a result, hedgers pay a premium to speculators and long positions in commodity futures are expected to earn excess returns. (Miffre 2016).

The theory of normal backwardation has not received much empirical support. Kolb (1992) finds that from 28 commodities, 9 have positive and significant average returns, whereas 4 have negative and significant returns. Main, Irwin, Sanders & Smith (2018) study a more recent period from 1990 – 2014 and find that no commodity, from a sample of 19 total, has significant returns. For a portfolio of diversified futures, Fama & French (1987) and Gorton & Rouwenhorst (2006) found significant positive significant returns. However, more recent studies by Main et al (2018), Fernandez – Perez et al (2018) and Blocher et al (2018) all find insignificant returns for long-only diversified portfolios of commodity futures.

Hedging pressure theory by Cootner (1960) relaxes the assumption that hedgers are net short. For instance, some consumers need the commodity as input in production and enter long positions to safeguard against price rises. Similarly, producers with commitments to deliver commodities at fixed prices can hedge losses from price appreciation with long futures positions. Therefore, the term structure of futures prices and the risk premium depends on the aggregated position of hedgers, which may be net long or short. When hedgers are net short the futures price is set below the expected spot and speculators earn a premium by entering the opposing long contracts. If hedgers are net long, the futures price is set above the expected spot price and speculators earn a premium by entering the short futures position as the futures price is expected to fall as maturity approaches. Similarly, Hirshleifer (1988) argues that commodity producers bear nonmarketable risks and these idiosyncratic risks can influence the premium on commodity futures. The author develops a theoretical model, where speculators face trading costs and barriers for entry that limits their risk-taking capacity. Resulting in the fact that in a modified CAPM context commodity futures risk premium depends on the systematic risk, or beta, and residual risk conditional on hedging pressure.

In the US the large market participants must report their positions to the Commodity Futures Trading Commission (CFTC), which subsequently publishes aggregated position data for commodity futures among other derivatives. The CFTC data classifies market participants as commercials or non-commercials. The data is often used to construct hedging pressure measurements by assuming that commercials are hedgers and non-commercials are speculators. The hedging pressure hypothesis has received mixed evidence as well (Rouwenhorst & Tang 2012, Miffre 2016). Bessembinder (1992) applies the Fama-Macbeth (1972) regressions and finds that residual risk conditional on net hedging has explanatory power over returns of agricultural futures. De Roon, Nijman & Veld (2000) find that 7 commodities out of 9 have significant loadings on net hedging pressure on a time-series setting. However, Rouwenhorst & Tang (2012) replicate the tests of the aforementioned studies and find opposing evidence. Firstly in a cross-sectional setting, the authors find that residual risk does not command a premium. Second, on the time-series setting only 3 commodities out of a sample of 29 have significant loading on net-hedging pressure.

Similar contradictory evidence is presented by studies that form long-short portfolios that buy commodities futures, which have recently been sold by hedgers and sell commodities futures on which hedgers have net long positions (Miffre 2016). Basu & Miffre (2013) find supportive evidence, where 75% of different long-short strategies based on the positions of hedgers, speculators, or both deliver significant positive returns. Daskalaki et al (2014) find that the spread between contracts sold by hedgers and contracts bought is not significant. Similarly, Swymanowska et al (2014) find that sorting on hedging pressure delivers only marginally significant returns.

Kang, Rouwenhorst & Tang (2020) argue that the inconsistent results regarding the hedging pressure result from ignoring the fact that non-commercials are a heterogeneous group of market participants whose trading motives are distinct from insurance providers. The researchers provide evidence in line with this hypothesis as short-term variation in hedging pressure is found to be caused by liquidity demands of non-commercials who pursue trend following strategies. Commercials (hedgers) earn a premium by providing liquidity as the authors find that commodities that have been bought by commercials in the previous week deliver positive and significant returns in the following two weeks. The standard hedging pressure premium, where providing insurance to hedgers gives rise to a premium, is rediscovered using trailing lower frequency changes hedging pressure where liquidity provision is controlled for. The authors conclude that short term position changes are driven by the liquidity demands of speculators, whereas position changes or trends observed over longer intervals are driven by the insurance demand of speculators.

The third theory, the theory of storage by Kaldor (1939), Working (1949) and Brennan (1958), relates the risk premium to the level of inventories. The theory of storage posits that basis (the difference between the futures price and spot price) is a function of storage costs, interest foregone and convenience yield. The theory suggests that inventory acts as a buffer against the risk of stockout. Low inventories translate to higher spot price volatility and downward sloping futures term-structure. Gorton, Hayashi & Rouwenhorst (2013) confirm that the basis or slope of futures prices varies positively with the level of inventory. If the spot price is assumed to be constant the theory suggests that long positions in backwardated futures and short positions in contangoed securities provide a premium.

The theory of storage has received supportive evidence from numerous studies (Miffre 2016). Gorton & Rouwenhorst (2006) Erb & Harvey (2006) and Swymanowska et al (2014) all find that backwardated commodity futures deliver higher returns relative to contangoed commodity futures. Fama & French (1987) find that the commodity basis can predict subsequent risk premiums for individual commodities. Gorton et al (2013) find that sorting on inventory level delivers significant returns as low inventory commodities outperform high inventory commodities.

3.2 Commodities Futures Pricing

Some commodities can be considered as investment assets. This is to say that they are primarily held for investment purposes, not for consumption or to be utilized in manufacturing processes. The key difference between investment asset and consumption asset is there are no benefits from physically holding the asset. Put differently traders are willing to sell an investment asset and enter long futures if it is more attractive. For commodities gold and silver, for example, are usually held for investment as they have desirable optionality properties, where they tend to appreciate during stock market downturns. (Hull 2015: 104, 121). The futures price for an investment asset is given by the following formulas:

$$F_0 = (S_0 + U)e^{rT} \tag{7}$$

$$F_0 = S_0 e^{(r*u)T} \tag{8}$$

Where:

$F_0 =$ Futures price

$S_0 =$ Spot price of the underlying asset

$U =$ Present value of storage costs borne by the underlying asset

$u =$ Storage costs as a proportion of the spot price

$T =$ Time to maturity

Storage costs are embedded in the futures price to compensate inventory holders for carrying the commodity until maturity. For investment assets, the equality between right-hand-side and left-hand-side must hold, otherwise, arbitrage opportunities exist. For instance, should the forward price exceed the RHS and investors could buy the asset and short the futures contract locking a profit. A similar argument cannot be made for consumption assets where the asset is primarily used as input in manufacturing. Entities trading consumption assets need the physical asset itself and are reluctant to sell the commodity and enter in a long futures position as they would lose control of the asset. (Hull 2015, 120-121). Thus, owning the physical asset gives rise to a utility. The price for a consumption asset is then given by:

$$F_0 = S_0 e^{(r+u-y)T} \tag{9}$$

Where:

$y =$ convenience yield

For the consumption assets futures prices are further discounted as holding the asset is beneficial due to uncertainty regarding the availability of the asset in the future. Higher convenience yield reflects markets' expectation that shortages are likely to occur. On the other hand, if inventories are high, supply is abundant and the convenience yield is low. (Hull 2015: 123)

3.3 Commodity Spot and Term Premia

Szymanowska et al (2014) and Blocher et al (2018) decompose commodity futures returns into a spot premium and term premium. The spot premium is related to risks in the price of the underlying, while the term premium is related to changes in the commodity futures basis. Formally Szymanowska et al (2014) begin with the cost-of-carry relationship, which is the futures price with the following equation:

$$F_t^{(n)} = S_t\left(1 + Rf_t^{(n)}\right)^n \left(1 + U_t^{(n)}\right)^n - C_{t+n} \tag{10}$$

Where:

$F_t^{(n)} =$ Futures price for delivery at time t + n

$S_t =$ Spot price of the underlying commodity

$Rf_t^{(n)} =$ n – period risk-free rate at time t

$U_t^{(n)} =$ per period storage costs, in percentage of the spot price

$C_{t+n} =$ net dollar equivalent cash payment representing the convenience yield

The cost-of-carry representation is used to define the futures log (percentage) basis as

$$F_t^{(n)} = S_t e^{y_t^{(n)} * n} \tag{11}$$

With:

$$y_t^{(n)} = \frac{1}{n}\ln\{S_t\left(1 + Rf_t^{(n)}\right)^n\left(1 + U_t^{(n)}\right)^n - \frac{C_{t+n}}{S_t}\} \tag{12}$$

Where:

$y_t^{(n)}$ = Per period basis or also known as cost-of-carry for maturity n

Swzymanowska et al (2014) relate the per-period basis to a bonds n-period interest rate and note that it is also the slope for the term-structure of commodity futures prices. Another helpful interpretation is given by Koijen, Moskowitz, Pedersen & Vrugt (2018), who define carry as an asset's futures return assuming that prices stay the same until maturity. Similarly, Swzymanowska et al (2014) define the spot risk premium, return in excess of the one period basis, as:

$$E_t[r_{s,t+1}] = E_t[\ln(S_{t+1}) + \ln(S_t)] = y_t^{(1)} + \pi_{s,t} \tag{13}$$

Where:

$\pi_{s,t}$ = spot risk premium

Swzymanowska et al (2014) define the term premium as a deviation from the expectations hypothesis for the term structure of the basis using the following form (rates expressed in log form):

$$ny_t^{(n)} = y_t^{(1)} + (n-1)E_t[y_t^{(n-1)}] - \pi_{y,t}^{(n)} \tag{14}$$

Where:

$\pi_{y,t}^{(n)}$ = term risk premium

Swzymanowska et al (2014) and Blocher et al (2018) note that the spot premium can be captured by taking either long or short positions in the front contract for commodities, given it is usually substituted for spot (physical markets) due to their illiquidity. The authors also show that term premium can be captured, for instance, by taking a long position in a more distant contract for the commodity and a short position in the front contract of the same commodity, effectively a calendar spread. Both studies highlight that the decomposition is necessary as different factors likely drive the different premia. Subsequently, Blocher et al (2018) and Boons & Prado (2019), among others, have used calendar spreads as the measure for term-premia for various strategies.

3.4 Factor-based Commodity Pricing Models

Bakshi, Gao & Rossi (2017) build and examine a 3-factor commodity pricing model in order to price individual commodities and managed portfolios. All the factors effectively aim to capture spot premia, as they are implemented using front futures only. The first factor is a carry strategy that buys commodities that are the most backwardated, according to commodities basis, and sells the most contangoed commodities. The second factor is formed by a Momentum strategy that buys the highest quintile of commodities when sorted according to cumulative returns on the preceding year or 6 months, and shorts the lowest quintile. The final factor is an equally-weighted (EW) long-only portfolio of all commodities. Their model is motivated by the documented high average return on both carry and momentum strategies (Erb & Harvey 2006, Fuertes, Miffre & Rallis 2010 among others) and the equally-weighted factor is needed in order to capture cross-sectional variation from individual commodities. Their model is not rejected when pricing baseline or managed portfolios as the residuals and alphas of the regressions are not statistically different from zero. Formally the model is given by:

$$r_{P,t} = \alpha_P + \beta_{P,EW} EW_t + \beta_{P,Mom} Mom_t + \beta_{P,Carry} Carry_t + \varepsilon_{P,t} \tag{15}$$

Where:

$r_{P,t}$ = returns of the test asset

$\alpha_P \dots \beta_{P,TS}$ = a parameter vector (intercept and slope coefficients) estimated with OLS.

EW_t = the returns of an equally weighted long-only return on the commodities included in the study.

Mom_t = the returns on a long-short portfolio that buys the highest quintile return commodities and shorts the lowest quintile return commodities.

$Carry_t =$ the returns of a carry strategy that buys the most backwardated commodity quintile and shorts the most contangoed commodity quintile.

Furthermore, Bakshi et al. (2017) provide economic, risk-based reasons, for the documented overperformance of the carry and momentum strategies. The carry strategy is found to be negatively related to changes in aggregate equity market volatility. That is that when volatility in developed equity markets rises, the carry strategy performs poorly and the high average returns are rewarded for bearing this risk. The momentum factor is positively related to speculative activity in commodities markets. That is that when speculators (financial investors) increase investment activity in commodities markets, especially the long-leg of the commodity momentum strategies tends to perform better. The evidence suggests that speculators tend to increase their positions in commodity futures that have performed well in the past.

Swymanowska et al (2014) investigate the predictive power of various instruments, such as basis, momentum or volatility sorting, over the spot and term premia. Numerous sorting instruments, such as momentum, spot price volatility, inflation betas and liquidity are found to be capable of delivering significant term premia over contracts that mature at least 4, 6 or 8 months from the present. However, the authors prove with asset pricing tests that the returns delivered by alternative sorting instruments are effectively spanned by separate low and high basis portfolios, that buy calendar spreads for commodities with a below-median basis and above-median basis respectively. This to say, that when the low basis and high basis portfolios are controlled for, the alternative sorting criteria do not deliver significant abnormal returns (alpha). Therefore, Szymanowska et al (2014) suggest the following asset pricing model for commodity futures term premia.

$$r_{P,t} = \alpha + \beta_{P,Hterm} Hterm + \beta_{P,Lterm} Lterm \tag{16}$$

Where:

$r_{P,t} =$ the returns on the test asset

$\alpha_P \ldots \beta_{P,TS} =$ a parameter vector estimated with OLS.

$Hterm =$ Returns of the equally weighted calendar spread portfolio for 4, 6 or 8-month maturities on commodities with above-median basis.

$Lterm =$ Performance of the equally weighted calendar spread portfolio for 4, 6 or 8-month maturities on commodities with below-median basis.

4 LITERATURE REVIEW

Standard finance theory and models such as the CAPM suggests that investors base their decisions on the first two moments mean (expected return) and variance (a measure of risk). However, Kraus & Litzenberger (1976) among others note that CAPM is misspecified and augmented the model with a systematic co-skewness factor, which improved pricing accuracy. The co-skewness was motivated as an un-diversifiable factor, that takes into account the asymmetry of returns which rewards upside potential and penalizes downside risk with a higher required rate of return. However, with passing time it has become evident that individuals tend to remain undiversified and concentrate on positively skewed assets, which in turn has lead to the development of theoretical modes that explain/predict such an outcome based on what is now known as lottery preferences (Mitton & Vorkink 2007; Barberis & Huang 2008). For commodity futures, theoretical models that incorporate skewness preference, a typical lottery characteristic, into hedging decisions have also been developed (Gilbert, Jones & Morris 2006; Lien & Wang 2015). All in all, all the models predict a negative relation between skewness and returns.

In this section, the theoretical models that explain skewness preferences and outline the implications are examined, as they provide the rationale for a significant return spread between high and low skewness assets. Selective hedging and models that incorporate skewness preferences into hedging decisions are presented because these provide an explanation, why the negative relation between skewness and returns likely manifests in commodity futures markets. Finally, the section concludes with a literature review, where previous studies on the impact of skewness on subsequent returns, and results across different asset classes are examined.

4.1 Theories and Implications for Lottery Preferences

Early evidence of lottery-preferences are the favorite-longshot bias in horse track betting and popularity of lottery-games. In the favorite-longshot bias expected returns per dollar bet increase as the odds of winning given to a horse increase. Put differently the best strategies concentrate on betting on the favorites and tend to do well as the longshots (unlikely winners) are overpriced. Similarly, with lottery games, the expected return falls below the price of the lottery ticket and economic theory suggests that no one should buy lottery tickets, which is at odds with reality as lotteries tend to be popular. (Thaler & Ziemba 1988). Subsequently, lottery-like assets have been used in financial literature to describe assets, which have a small change of a large gain but poor expected returns.

Mitton & Vorkink (2007) formally show how lottery-preferences manifest in financial markets and their implications. The authors develop a model that depicts how a traditional investor and a lottery investor, with a preference for positively skewed assets, allocate their capital. Their model predicts that the lottery investors hold less diversified portfolios, is willing to decrease the portfolios Sharpe ratio for potential bigger upside and concentrates on holding assets with high idiosyncratic skewness. The authors test these predictions on data provided by a large US brokerage house. Their sample spans from 1991-1996 and consists of information regarding the brokerage accounts of roughly 56000 individual investors. The authors prove that individual investors purposely choose to remain undiversified and hold the most highly skewed assets. This decision is largely motivated by the fact that in the sample the highest performers in terms of average returns are undiversified lottery-type investors. The strong performance does come at the cost of the individual portfolios Sharpe ratios and poor expected returns which are negatively associated with lack of diversification and idiosyncratic skewness of assets.

Brunnermeier, Gollier & Parker (2007) investigate a model where investors choose to hold distorted beliefs about the likelihood of future economic states and derive utility from investing optimally in accordance with their beliefs. Anecdotally, in the authors' model, the representative investor perceives the state with the most positively skewed outcomes for wealth highly likely due to optimism. The investor invests in a manner that increases his consumption in the positively skewed state and subsequently believes more strongly that the unlikely state comes to pass. The authors conclude that should investors invest in accordance with their model, base investments on optimistic beliefs, then securities with positively skewed returns tend to become overpriced and have poor expected returns.

Barberis & Huang (2008) develop a model in which investors derive their utility under the cumulative prospect theory of Tversky & Kahneman (1992). Under cumulative prospect theory, investors have convex utility functions over losses and concave over profits. In addition, investors apply a probability-weighting scheme that places higher values on low probability events. Under these conditions, investors prefer assets with positive skewness since these assets provide a small chance of a large payoff. Similarly, investors are unlikely to diversify as it cuts of the upside potential, for which these investors grant the highest utility. Similarly to the model of Brunnermeier et al (2007), the Barberis & Huang (2008) model implies that assets whose returns are positively skewed become overpriced and deliver poor returns.

4.2 Selective Hedging and the Impact of Skewness Preference

Stulz (1996) presents a mechanism called selective hedging, which could incorporate skewness preferences in the commodity futures markets. Selective hedging means that the subjective views of risk managers are taken into account and affect how much of uncontrollable outside exposures are hedged. Stulz (1996) expands the term by stating that the purpose of risk management should be to clip the left tail (buy deep out-of-money puts) or to avoid disasters. Such a practice would limit the probability and expected costs of distress scenarios while maintaining some beneficial exposure to systemic factors.

Stulz (1996) argues that firms, especially ones with potential comparative advantage, strong capital structure and concentrated ownership would benefit the most from selective hedging. Some firms, commodity producers, for example, might generate advantageous information about future prices through their operations and could potentially benefit from taking speculative positions relative to full-hedges. Firms with a more robust capital structure can afford potential losses from speculation as they do not materially impact the likelihood of distress. In addition, firms with concentrated ownership benefit from selective hedging as the owners have larger portions of wealth tied to the firm and diversification across other assets is not possible. Selective hedging, when properly implemented, limits the downside risks while maintaining exposure to beneficial tailwinds.

Gilbert, Jones & Morris (2006) further show how skewness has an impact on commodity futures demand by developing an analytical model in which producers choose a hedge ratio to maximize their expected utility. In the model, producers maximize the expected utility with preferences on mean, variance and skewness of their profit distribution by choosing a quantity of forwards sold. The profit distribution depends on the forward price and the uncertain future spot price. The authors calculate and compare hedge ratios of their model and a traditional mean-variance model based on cotton price data. Hedge ratios vary in accordance with the forward bias (forward price systematically differs from the expected spot in either direction), skewness of the spot price and the risk aversion of the investor. When there is no forward bias both models suggest full hedges, as speculation is not profitable. The table below presents the outcomes for 4 different scenarios: positive or negative forward bias coupled with positive or negative spot skewness. Speculation is defined as the difference between a full hedge and optimal hedge according to the models:

Table 1: Hedging decisions based on futures price bias and skewness scenarios

F < E(S) , negative skewness	Preference for skewness increases forward selling (less speculation)
F > E(S) , positive skewness	Preference for skewness reduces forward selling (less speculation)
F > E(S) , negative skewness	Preference for skewness increases forward selling (more speculation)
F < E(S) , positive skewness	Preference for skewness reduces forward selling (more speculation)

Gilbert et al (2006) also provide the economic rationale for all scenarios. In the first case (backwardation, negative skewness) a mean-variance investor would reduce hedging (sell less forwards) since the end of the period spot prices tend to exceed the future price and unhedged positions tend to be profitable. If the spot price is negatively skewed the producer will increase forward selling as there is a higher likelihood of the end of period spot falling below the futures price. The opposite holds for the second case, the mean-variance producer would sell more forwards to lock the upwards biased futures price. If positive skewness is added, the producer will sell fewer futures as the profit opportunities from speculation suffer from the higher likelihood of a spot price increases at maturity. In the last two cases, skewness increases speculation (hedge differs more from a full hedge). For instance, if the forward price is upwards biased and the future spot negatively skewed, the producer will sell more forwards, since negative skewness hurts positions left unhedged. Should the forward price be downwards biased and the spot positively skewed, the producer will hedge considerably less or even buy the forward (given low risk aversion). In all cases, positive skewness reduces net short-selling and negative skewness increases it.

Lien & Wang (2015) similarly develop an analytical model that incorporates preferences for higher moments and in addition fit spot prices to a generalized hyperbolic skewed Student T-distribution. The skewed Student T-distribution is asymmetric and has heavy tails (higher likelihood of extreme outcomes). Furthermore, the skewed tail is considerably heavier than the other. The authors motivate the use of their distribution by pointing to mounting evidence that financial returns are not normally distributed and that extreme outcomes are relatively frequent. The authors simulate hedge rations by altering skewness and forward prices (similarly as in Gilbert et al 2006) and find that producers will always hedge more (less) when negative (positive skewness) prevails.

4.3 Previous Studies

Kraus & Litzenberger (1976) develop a three-moment capital asset pricing model which adds an assets' co-skewness with the market to the original CAPM. The authors argue that adding co-skewness improves asset pricing accuracy. Assets' co-skewness signifies the contribution of the asset to the skewness of the market portfolio, for instance, high co-skewness asset increases the skewness of the market portfolio. Kraus & Litzenberger (1976) find that the three-moment CAPM manages price beta and co-skewness sorted portfolios formed using NYSE stocks during 1936-1970, a period where the traditional CAPM fails (significant intercept). Thus, the authors provide evidence that investors prefer positively skewed assets and are willing to accept lower returns on them.

Harvey & Siddique (2000) modify the 3-moment CAPM with a conditional co-skewness factor. Co-skewness is calculated in a similar manner to covariance (or standard beta) except market returns are in quadratic form and 60-month residuals, from regressing the stock on CAPM, are used instead of historical excess returns. Conditional co-skewness, is therefore a forward-looking estimate of future co-skewness. The authors find that a hedge portfolio, that buys the lowest co-skewness tercile and sells the highest co-skewness tercile, yields a 3,6% annual excess return. Furthermore, adding a co-skewness factor improves the explanatory power of the Fama & French 3-factor model when industry, size, book-to-market and momentum portfolios are used as test assets. Finally, momentum is found to be linked to co-skewness as recent winners tend to have lower skewness, and as such the strong performance of momentum could be attributed to the reward for bearing negative skewness and the associated crash risk.

Christie-David & Chaudhry (2001) investigate the significance and explanatory power of co-skewness (and co-kurtosis) within commodity futures markets. Using a cross-sectional approach similar to Kraus & Litzenberger (1976) and Fama & Macheth (1973), Christie-David & Chaudhry (2001) find that co-skewness is priced and significant, with a negative coefficient, in the cross-section of commodity futures. The authors show that adding a co-skewness and co-kurtosis improve the explanatory power over the traditional CAPM model, significantly from 7% to 13% with co-skewness added, and to 22% with co-kurtosis added on top. Thus, the authors prove that investors in commodity futures markets also value positive skewness and demand a premium for holding negatively skewed assets.

Xing, Zhang & Zhao (2010) construct a daily skewness estimate for individual US stocks using options. The authors measure the slope of implied volatility or its “smirk” (which the authors call SKEW) by extracting the implied volatility of an at-the-money call from the implied volatility of an out-of-the-money put. In the option setting higher implied call volatility, is interpreted as increased upside probability similar to positive skewness. High put volatility, means that investors are expecting the price of the underlying to decrease or crash. In the authors setting a higher positive value of the volatility, smirk implies a higher expected likelihood of negative developments (similar to negative skewness). Using weekly firm-level Fama-Macbeth regressions the loading on SKEW is found to be significant and negative, which suggests that positively skewed assets (higher call implied volatility) deliver higher returns. The authors employ a trading strategy that buys the quintile of stocks that have the most expensive calls and sells stocks with relatively expensive puts. The strategy yields a significant and positive weekly return of 16 basis points (9,19% annualized) and a significant Fama & French 3-factor alpha of 21 basis points (10,90% annualized). The results are at odds with the downside risk premium and lottery preferences as positively skewed stocks (with relatively expensive calls) outperform the counterpart.

Cremers & Martin (2010) perform similar analyses by examining the relation between implied volatility spread extracted from options and firm stock returns on the following week in the US. The authors calculate daily volatility spreads (VOL spread) as the difference between the implied volatility of a pair of matching call and put options by strike price. Numerous pairs are employed per spread by summing the open interest weighted option pairs and firms are subsequently sorted into 5 quintiles by the volatility spread. The researchers carry out analyses for both weekly and 4-week holding periods. The authors investigate the performance of a hedge portfolio that buys the highest VOL spread portfolio (level and change) and shorts the low VOL spread portfolio (level and change).

The hedge portfolio earns an average weekly return of 50 basis points and a five factor-alpha of 50 basis points, where factors included are the Fama & French 3-factors, Carhart (1997) momentum, and Harvey & Siddique (2000) co-skewness. Therefore, the results of Cremers & Weinbaum (2010) are consistent with those of Xing et al (2010), where stocks with high VOL spread (relatively expensive calls) outperform stocks with low VOL spread (relatively expensive puts) and present contrary evidence to the skewness preference argument.

Boyer, Mitton & Vorkink (2010) present a model to calculate expected idiosyncratic skewness and investigate its relation to subsequent returns. The authors argue that, contrary to standard finance theory, investors prefer holding assets with high asset-specific skewness as these assets have the highest earnings potential, which suffers from diversification. The ex-ante firm-level skewness measure is calculated using predictive regressions. First Fama-French 3 factor model is run on stock returns using monthly data and 60 monthly (5-years) observations. The residual from the regression is raised to the second and third power to obtain estimates for both idiosyncratic volatility and skewness. Then the authors construct a predictive regression model to estimate idiosyncratic skewness, where the predictive variables include idiosyncratic volatility and skewness, momentum, turnover, and dummies for NASDAQ and firm size. Firms are sorted into quintiles according to the predicted idiosyncratic skewness and the authors discover using time-series regressions that a strategy that buys low expected idiosyncratic skewness and shorts high expected idiosyncratic skewness yields an average significant return of 67 basis points per month. Additionally, the skewness strategy yields a monthly significant Fama & French 3-factor alpha of roughly 1%. Utilizing Fama-Macbeth regressions the expected idiosyncratic skewness factor persists when controlling for known risk-premiums.

Bali, Cakici & Whitelaw (2011) study whether a relation exists between previous months' maximum daily returns (MAX) and monthly returns on stock portfolios and individual stocks. The researchers argue that the maximum daily return resembles a lottery characteristic, high potential upside with a negative expected return, that investors prefer.

The authors utilize a sample of US stocks and the sample period spans from 1962-2005. Using time-series regressions the authors find that a long-short portfolio that buys the highest max stocks and shorts lowest max stocks yields a significant average monthly return of -1% in the next month. The results are more significant if the average of 5 maximum daily returns is used. In addition, the authors run monthly Fama-Macbeth regressions on firm-level returns and find that the MAX effect is significant with a negative coefficient. The results provide supportive evidence for lottery-preference theories where investors tend to concentrate on stocks with positive extreme payoffs which hinder future performance.

Conrad, Dittmar & Ghysels (2013) use options data to construct forward-looking risk-neutral estimates of stock return moments. Their analysis uses US stock and options data for the period 1996-2005. The authors calculate risk-neutral moments using options that mature in 1, 3, 6 and 12-months and average the daily observations for each quarter. The authors discover that using a tercile sort on skewness, the return spread between high risk-neutral skewness portfolio and its low counterpart yields a significant -82 basis points return on the next calendar quarter. The results are significant when using options with 3-months to maturity and marginally significant using options with 12-months to maturity. Using the same strategy and Fama & French 3-factor asset pricing model the skewness sorting leads to a significant -1,1% alpha assuming the portfolio is held for the next calendar quarter. Similar results hold when the authors construct risk-neutral idiosyncratic, ie firm-specific diversifiable risk moment estimators, sorting on idiosyncratic skewness yields a marginally significant raw return of -67 basis points for the following quarter and a significant Fama & French 3 factor-alpha of -1%. Finally, the authors discover that firms with high risk-neutral skewness tend to have higher valuation ratios (lower earnings-to-price) suggesting that investors tend to prefer positive skewness and overprice them.

Amaya et al. (2015) investigate the relation between historical return moments and subsequent stock returns. The authors use high-frequency intraday data and argue that this provides improved precision relative to historical data with lower frequency. The sample consists of US stocks and the period is 1993-2013. The authors construct moment estimators based on realized volatility which is calculated by using 5-minute returns that are aggregated for a 1-week period. The authors perform regressions in order to study the time-series performance and cross-sectional persistence of skewness portfolio that buys high skewness and sells short low skewness deciles. The average time-series return for the skewness portfolio is -19 basis points (value-weighted) and highly significant for weekly holding periods. The skewness portfolio is significant in Fama-Macbeth regressions and the coefficient is negative. The authors run double sorted regressions using realized skewness and volatility and find that the reward for negative skewness increases with volatility, which is expected as together they imply a higher likelihood of extreme downside events.

Barinov (2018) challenges the evidence presented by Bali et al. (2011) and Boyer et al (2010). The researcher argues that lottery stocks tend to be firms, which have option-like equity or growth options and are convex investments. As such lottery stocks, proxied by the MAX effect and idiosyncratic skewness (IDIOSKEW), act as insurance against unexpected rises in aggregate volatility because in such conditions the option-likeness becomes more valuable. The author investigates the characteristics of lottery-like stocks and finds that the extreme quintile (high MAX, high IDIOSKEW) or short leg of the strategies consists of firms that have worse credit ratings and higher bankruptcy probability as indicated by the O-score relative to the opposing extreme quintile. The author constructs an aggregate volatility factor (FVIX) that has a high correlation with changes in VIX (0,715) and is a significant predictor of NBER recessions. Finally, once the FVIX factor is included in time-series asset pricing regressions (Carhart 4) it remains negative, significant and eliminates the significant abnormal returns (alphas) earned by the MAX and IDIOSKEW hedge portfolios. The evidence suggests that lottery stocks act as hedges against unexpected volatility, which is why they earn low expected returns as opposed to investor demand for lottery-likeness.

This thesis builds largely upon the research of Fernandez-Perez, Frijns, Fuertes & Miffre (2018), who argue that due to selective hedging skewness of daily returns is informative of future expected returns in commodity futures. Selective hedging stands for a practice, where the subjective views of the investor influence the hedging decisions of commodity producers and consumers (Stulz 1996). Fernandez-Perez et al (2018) argue that due to both lottery preferences and selective hedging practices negatively skewed commodity futures are sold in excess, or effectively underpriced. Positively skewed commodity futures are sold more rarely, which leads to overpricing.

Fernandez-Perez et al (2018) study whether commodities futures daily realized skewness is related or predictive to the futures expected returns. The authors use a sample consisting of 27 futures for a period ranging from 1987-2014. Skewness is measured as the realized daily returns skewness over the previous 12 months. The authors implement a trading strategy that goes long on the most negatively skewed front-end commodity futures and short on the most positively skewed front-end commodity futures. The strategy generates an average annual excess return of 8,01% and an alpha of 6,21% per year over a period ranging from 1987 – 2014. Furthermore, the authors apply the Fama-Macbeth regressions in order to see whether a skewness factor commands a risk premium in the cross-section of commodity futures. The skewness factor has a significant average risk premium of 5,02% per annum and improves the r-squared of different asset pricing models on average by 3,5%. The authors conclude that their findings support the theory of skewness preferences and selective hedging.

Jondeau, Zhang & Xiaoneng (2019) study the relation between skewness and market-level returns in the US. The authors argue that skewness can lead to market level return predictability as retail investors concentrate on lottery-stocks and skewness can proxy for tail or crash risk. Firm-level skewness is calculated using daily returns for monthly periods and averaged based on both value-weighting and equal-weighting. The authors run predictive regressions where the market return is regressed on previous months' average skewness. Average skewness turns out to be a statistically and economically significant predictor of market returns and the relation is negative. On average a standard deviation increase in average monthly skewness leads to a 52 basis points decrease on market returns on the following month. Furthermore, when the market return is above (below) it's mean and skewness is below (above) its mean, the following months market excess returns stand at 1,14% (-0,18%) on average. As a robustness check the authors implement a trading strategy that uses skewness models prediction in assigning proper weights to the market portfolio. The strategy yields an annualized 15,8% return and 0,62 Sharpe ratio when using a predictive model based on value-weighted skewness. For comparison, a strategy based on predictions using value-weighted mean return alone yielded an annual return of 10.5% and Sharpe ratio of 0,50.

Studies presented so far focus on the relation between skewness and subsequent returns on short horizons (monthly to yearly). Bessenbinder (2018a) points out that on longer time horizons the relation shifts and positive skewness becomes a key determinant in delivering returns. Analyzing buy-and-hold returns on common US stocks ranging from the period 1926-2016 Bessenbinder (2018a) finds that most stocks fail to generate returns in excess of corresponding one month T-bills. Only 42,6% of stocks listed in the US have larger average returns than that of 1-month T-bills. The results are driven by positive monthly return skewness, which in turn is amplified due to compounding. Resulting in the fact that the observed stock market mean excess returns are driven by relatively few positively skewed stocks. Using bootstrapping simulations, the author also proves that return skewness tends to decrease and mean returns increase when more stocks are added to the portfolio. The results indicate that actively managed strategies tend to underperform as they are poorly diversified. The benefits of diversification are largely due to increasing the amounts of stocks held increases the ex-ante chance of holding the most positively skewed stocks that generate the most wealth over longer time periods.

5 DATA AND METHODS

The data on commodities is downloaded from Datastream and the specifics are listed in table 1. The period ranges from March 1996 to October 2019. For return series construction the methodology of Szymanowska et al (2014) is applied and continuous return indexes are constructed for contracts that do not mature at least in 2, 4, 6 and 8 months. The choice of using two-months as the roll point was motivated by Szymanowska et al (2014) who note that the futures prices behave erratically both on the maturity month and the month before as traders begin rolling over their positions 4 – 6 weeks prior to maturity. To facilitate comparison with the results of Fernandez-Perez et al (2018) returns are also compiled rolling a month before maturity and reported in the appendix.

Table 2: List of commodities

Contract name	Date	Maturities used	Series	Exchange	Sector
Heating oil	3.1996	All months	4	NYMEX (CME)	Energy
Light crude oil (WTI)	3.1996	All months	4	NYMEX (CME)	Energy
Natural gas	3.1996	All months	4	NYMEX (CME)	Energy
Gasoline	1.2006	All months	4	NYMEX (CME)	Energy
Corn	3.1996	3, 5, 7, 9, 12	4	CBOT (CME)	Grains
Oats	3.1996	3, 5, 7, 9, 12	3	CBOT (CME)	Grains
Rough rice	3.1996	1, 3, 5, 7, 9, 11	3	CBOT (CME)	Grains
Wheat Chicago	3.1996	3, 5, 7, 9, 12	4	CBOT (CME)	Grains
Cotton2	3.1996	3, 5, 7, 10, 12	4	ICE	Industrials
Lumber	3.1996	1, 3, 5, 7, 9, 11	3	CME	Industrials
Feeder Cattle	3.1996	1, 3, 5, 8, 9, 11	3	CME	Meats
Lean Hogs	3.1996	2, 4, 6, 8, 10, 12	4	CME	Meats
Live Cattle	3.1996	2, 4, 6, 8, 10, 12	4	CME	Meats
Copper	3.1996	3, 5, 7, 9, 12	4	NYMEX (CME)	Metals
Gold	3.1996	2, 4, 6, 8, 10, 12	4	NYMEX (CME)	Metals
Platinum	3.1996	1, 3, 7, 10	2	NYMEX (CME)	Metals
Palladium	3.1996	3, 6, 9, 12	2	NYMEX (CME)	Metals
Silver	3.1996	1, 3, 5, 7, 9, 12	4	NYMEX (CME)	Metals
Soybean	3.1996	1, 3, 5, 7, 9, 11	4	CBOT (CME)	Oil seeds
Soybean meal	3.1996	1, 3, 5, 7, 9, 12	4	CBOT (CME)	Oil seeds
Soybean oil	3.1996	1, 3, 5, 7, 9, 12	4	CBOT (CME)	Oil seeds
Cocoa	3.1996	3, 5, 7, 9, 12	4	ICE	Softs
Coffee	3.1996	3, 5, 7, 9, 12	4	ICE	Softs
Orange Juice	3.1996	1, 3, 5, 7, 9, 11	4	ICE	Softs
Sugar11	3.1996	3, 5, 7, 10	4	ICE	Softs

As an example of the series construction consider Corn, which has contracts trading for delivery in March, May, July, September and December. During May the front contract is for delivery in July, the second nearest (4 months) contract expires in September, and the third (6 months) and forth (8 months) expire in December and March in the following year. Since the delivery of the front-end contract falls within two months after may, the front series rolls from the July contract to the September contract at the end of March. All other series roll similarly to the next nearest contracts according to the two-month interval. As noted by Blocher et al (2018) the entire futures curve is rolled during roll dates and some contracts are skipped for commodities with monthly deliveries, but all contracts listed in table 2 will be used at some point throughout a calendar year.

The selection of maturities used per commodity for return series construction, as well as the number of series, is also based on the selection of Szymanowska et al (2014) available on their internet appendix. For most commodities, all 4 time-series can be constructed with the exceptions being Oats, Rough rice, Lumber, Feeder cattle, Palladium and Platinum. For these commodities, the daily trading volume decreases substantially for more distant maturities and to avoid analysis based on thinly traded prices less return series are constructed. In total, all 25 commodities have return series for the first nearby (2 months till expiry) and second nearest (4 months till expiry). For the third nearest (6 months till expiry) the amount decreases to 23 and for the fourth nearest (8 months till expiry) to 16 commodities.

5.1 Spot and Term Premia Calculations

Commodity return series represent excess returns and the calculations are based on settlement prices as in Fernandez-Perez et al (2018) and Gorton, Hayashi & Rouwenhorst (2013) among others. The standard excess returns can be thought of as a strategy where long positions are held in the front contract until the designated roll date. Upon the roll date, the first contract is sold at the settlement price, which incurs a profit or a loss, and a long position is entered into on the second nearest contract at the settlement price, which does not incur gains or losses on the roll date. On the following day or month profit calculations will depend on the settlement prices of the contract that has now become the first nearby. Put differently, the excess return calculations are always based on settlement prices from a single contract per commodity. Fully collateralized futures positions are assumed and the returns are quoted in excess of the risk-free rate. The daily excess returns are given by the following formula.

$$r_{i,d,t} = \ln\left(\frac{F_{i,d,t}}{F_{i,d-1,t}}\right) \tag{17}$$

Where:

$F_{i,d,t}$ = the futures price for commodity i, on day d or month t

$r_{i,d,t}$ = the spot return for commodity i, on day d or month t

The excess returns are calculated also for monthly intervals in a similar manner using the end of month settlement prices. As in Szymanowska et al (2014) and Boons & Prado (2019) returns in the first nearby contracts (2 months till maturity) are taken as the spot premium and are denoted as $r_{i,t}^{n1}$. N2, N3 and N4 denote the excess returns for the 4-month, 6-month and 8-month series. The spot premium represents a near-term price risk of the underlying asset.

The term premium is captured by taking a short position in the front contract and a long position in a more distant contract as in Szymanowska et al (2014), Blocher et al (2018) and Boons & Prado (2019) among others. The term premium represents risks or changes related to the commodity basis and can be thought of as expected deviations from the expectations hypothesis, due to changes in convenience yield or storage costs for example. The spreading returns are calculated for each of the three more distant maturity series as:

$$r_{i,t}^{spr2} = r_{i,t}^{n2} - r_{i,t}^{n1} \tag{18}$$

Where:

$r_{i,t}^{n2}$ = the excess returns on the second nearest contract for commodity i, during mont t

$r_{i,t}^{n1}$ = the excess returns on the first nearby contract for commodity i, during mont t

SPR2, SPR3 and SPR4 denote spreading returns going long on the 4-month, 6-month and 8-month contracts respectively while taking a short position in the front contract.

Since individual commodities and portfolios that consist of commodity futures vary drastically in terms of returns and risk, the Sharpe ratio is also calculated for all assets in this thesis. The Sharpe ratio expresses how much return did an asset or strategy deliver per unit of risk in the sample, and makes strategies that behave differently more comparable. Higher Sharpe ratios are preferable to investors. The formula for the Sharpe ratio used in this thesis is the following

$$\text{Sharpe} = \frac{\mu}{\sigma} \tag{19}$$

Where

$\mu =$ the average excess return (spot or spreading depending on strategy) of the strategy or asset in the sample.

$\sigma =$ standard deviation of the return by the strategy or asset in the sample.

Since all returns in the thesis are quoted in excess return form the risk-free rate does not enter the equation. Usually, especially in equity-related literature, the risk-free rate is subtracted from the denominator to obtain excess returns.

5.2 Skewness Based Spot and Term Strategies

The main interest of this thesis is to analyze the performance of the skewness-strategies based on the instrument proposed by Fernandez-Perez et al. (2018). In the spot return context, this strategy buys the quintile of commodities that exhibit lowest daily return skewness over the previous year and sells the highest quintile. The holding period for the skewness portfolio is one month and rebalancing takes place at the end of each month. The methodology for constructing the skewness signal is the same as in Fernandez-Perez et al. (2018) applying the Pearsons coefficient of skewness, which is used as the sorting signal for commodities and is given by the following formula.

$$Sk_{i,t} = \left[\frac{1}{D}\sum_{d=1}^{D}(r_{i,d,t}^{n1} - \mu_{i,d,t})^3\right] / \sigma_{i,t}^3 \tag{20}$$

Where:
$r_{i,d,t}^{n1} =$ are daily spot excess return observations on commodity i over the time period t = [t-11, t]
$\mu_{i,d,t} = \frac{1}{D}\sum_{d=1}^{D} r_{i,d,t}^{n1} =$ estimated mean of daily spot excess return observations over the 12-month window.
$\sigma_{i,d,t}^2 \sum_{d=1}^{D}(r_{i,d,t}^{n1} - \mu_{i,d,t})^2 =$ estimated variance of daily spot excess return observations over the 12-month window.

The return predictability of skewness is also examined in the term-premia context. In the term premia setting the skewness of daily excess returns for the front contract are used as criteria to sort commodities into two portfolios, one below the median LowSkew and one above the median HighSkew. The different sorting scheme (from quintiles to above and below basis) is done to facilitate comparison with previous results that explore term premia by a variety of instruments as in Szymanowska et a. (2014). Both LowSkew and HighSkew portfolios are examined using the three different maturities of $r_{i,t}^{spr}$ and their equal-weighted average, where the signal is still based on the skewness of daily spot returns of the front contracts.

5.3 Methodology and Control Factors

The first testing phase consists of calculating descriptive statistics on both the strategy and different factors. The one-sample student T-test is applied to the returns of the individual commodities, skewness strategy and factors to test whether their average returns are statistically different from zero. For the second hypothesis, the spot returns earned by the Skew strategy are regressed on the Bakhsi et al. (2017) commodity pricing model to see whether the strategy generates a significant alpha or put differently the returns of the strategy are not explained with known risk factors or strategies. The pricing model has the following form:

$$r_{Skew}^{n1} = \alpha_P + \beta_{Skew,EW} EW_t + \beta_{Skew,Mom} Mom_t + \beta_{Skew,TS} TS_t + \varepsilon_P \tag{21}$$

Where:

r_{Skew}^{n1} = denotes the return of the long-short skewness portfolio on month t.

$\alpha_{skew} \dots \beta_{skew,}$ = a parameter (intercept + loadings) vector with respect to each factor estimated with OLS.

EW_t = the returns of an equally weighted long-only return on the commodities included in the study.

$Carry_t$ = a strategy (also called term-structure in Fernandez- Perez et al. 2018) that buys the most backwardated commodity quintile and shorts the most contangoed commodity quintile.

Mom_t = the returns on a long-short portfolio that buys the highest quintile return commodities and shorts the lowest quintile return commodities.

The factors are constructed in a similar fashion as in Bakshi et al (2017). The EW-factor is a long-only portfolio that equally weights all commodities in the sample. The carry factor sorts commodities according to $Basis = \ln\left(\frac{F_{n2}}{F_{n1}}\right)$, where a negative ratio means that the futures price of the front contract is higher than the second nearest and the term-structure is backwardated and vice versa for positive ratio, which signifies contango. At the end of every month, the Carry portfolio buys the most backwardated quintile and shorts the most contangoed quintile. The Momentum (Mom) factor sorts commodities by their cumulative return over the previous 12-months and the recent winners are bought and the losers are shorted. All factors are rebalanced monthly at the end of the month.

Similar time-series asset pricing regressions are run for the term-premiums earned by the LowSkew and HighSkew portfolios. The control factors are based on the findings of Szymanowska et al (2014) and Blocher et al (2018) who find that using the basis, measured at the front of a commodities futures curve (similarly as in Carry), as a sorting signal to divide commodities into two portfolios, Lterm for commodities with a basis below the median and Hterm for commodities with a basis above the median. Both studies find that the two term structure factors spanned the returns of portfolios that used alternative sorting instruments. The model has the following form

$$r_{Skew}^{spr2}, r_{Skew}^{spr3}, r_{Skew}^{spr4} = \alpha + \beta_{P,Hterm} Hterm + \beta_{P,Lterm} Lterm + \varepsilon_P \tag{22}$$

Where:

r_{Skew}^{spr} = denotes the spread returns earned by the LowSkew and HighSkew portfolios using different maturities to implement the calendar spreads

$\alpha_{skew} \ldots \beta_{skew}$ = is the loading to the factor denominated by subscript estimated with OLS

$Hterm =$ Returns of the equally weighted calendar spread portfolio for 2, 4 and 6-month maturities on commodities with above-median basis.

$Lterm =$ Performance of the equally weighted calendar spread portfolio for 2,4 and 6-month maturities on commodities with below-median basis.

As a clarification, all the factors base the sorting variable on the historical spot (first nearby) return/price data. Skew, EW, Carry and Mom represent long-short strategies that buy and sell only the front contracts, which captures the spot premiums. LowSkew, HighSkew, Hterm and Lterm represent long-short strategies that implement calendar spreads, meaning short positions in the front contract and long positions in farther maturities, as the spreads capture the term premium (Szymanowska et al 2014, Blocher et al 2018).

6 EMPIRICAL RESULTS

This section first provides the descriptive statistics for spot premia for individual futures contracts to provide a background on how individual futures faired during the sample. Then characteristics of realized spot return skewness are examined and the frequency of commodities in the extreme skewness portfolios are presented to facilitate comparison with the research by Fernandez-Perez et al (2018) and to ensure that the results aren't driven by a minority of commodities. Finally, the descriptive statistics for the alternative factors in both spot and term premia are investigated as well as the time-series regressions to analyze the risk-adjusted returns of the skewness strategies.

6.1 Descriptive Statistics for Commodity Spot Premia

Descriptive statistics for the excess return of the front contracts are reported in table 3. The key takeaway is that none of the 25 commodities included in the study have a significant positive excess return over the period March 1997 – October 2019, evident in the lack of larger positive T-statistics (1,97 being cutoff for significant at 0,05 level). Palladium has the most attractive return characteristics with an average annual return of 10,7% and Sharpe ratio of 0,31 on a collateralized basis, however, the return is not even marginally significant with 1,51 t-statistic (p-value 0,13). On the other hand, rough rice, wheat and lean hogs have statistically significant negative annual returns of -11,1%, -13,9% and -11,2% respectively. In addition, corn and lumber have marginally significant (t-stat higher than 1,65, or p-value less than 0,10) negative returns. Similarly, the volatile nature of commodities is evident, as the annual volatility ranges from 14,% with feeder cattle to 42,7% of natural gas. The volatility results are similar to that of Kat & Oomen (2007), who also report a rough average of 30% annual volatility for commodities.

The descriptive statistics for the returns of individual front commodity futures are inline with the results reported in Erb & Harvey (2006) and Main et al (2018), who also find that either very few or none of the commodities has significant positive returns. Therefore the initial results are against the theory of normal backwardation (Keynes 1930 among others), which assumed that futures price were downward biased and a premium would be rewarded for the long-side as reimbursement of price risk. The sample contains a commodity boom and bust cycle as the prices of commodities increased substantially at the beginning of the 2000th century due to increased demand from developing economies and financialization (Ke & Tang 2012). Commodity prices peaked during the financial crises and sovereign debt crises and have tended to decline post-2014. A potential reason for the poor performance of individual commodities is the low level of inflation experienced during the sample period. Levine, Ooi, Richardson & Sasseville (2018) document that inflation is a key driver for commodity returns and that high inflation is associated with high return for commodity futures.

Descriptive statistics for the farther maturity excess returns are reported in the Appendix (second table). Overall for all farther maturity series, significant returns also tend to be rare and the returns are usually indistinguishable from zero in statistical terms. However, interestingly both the annual mean arithmetic returns and their standard deviations tend to decrease as the time to maturity increases as predicted by Samuelson (1965). Returns are also reported using the 1-month rolling methodology applied in Fernandez-Perez et al (2018) for the front contract of commodities and the results are reported in the first table of the Appendix. The results are largely unchanged with 3 commodities yielding a significant negative return and only 1 commodity yielding a positive and marginally significant annual return.

Table 3: Descriptive statistics for N1 (front) excess returns. The mean is the average annualized excess return. T-stat represents the test statistic against the hypothesis that the mean return equals zero. Std is an annualized standard deviation of excess returns. Sharpe represents risk-adjusted returns and is calculated by dividing annualized mean with annualized standard deviation The asterisk *,**,*** represents significance at the 10, 5,1% level respectively.

	Commodity	Mean	T-stat	Std	Sharpe
Energy					
	Gasoline	-0,005	-0,060	0,308	-0,016
	Heating oil	0,040	0,660	0,294	0,136
	Light crude oil (WTI)	0,037	0,573	0,311	0,118
	Natural gas	-0,142	-1,613	0,427	-0,332
Grains					
	Corn	-0,097*	-1,752	0,269	-0,361
	Oats	-0,036	-0,581	0,303	-0,120
	Rough rice	-0,111**	-2,268	0,237	-0,467
	Wheat	-0,139**	-2,308	0,292	-0,475
Industrials					
	Cotton2	-0,092*	-1,667	0,269	-0,343
	Lumber	-0,111*	-1,876	0,288	-0,386
Meats					
	Feeder Cattle	0,015	0,469	0,152	0,096
	Lean Hogs	-0,112**	-2,108	0,257	-0,434
	Live Cattle	-0,008	-0,275	0,143	-0,057
Metals					
	Copper	0,035	0,644	0,261	0,133
	Gold	0,031	0,940	0,162	0,194
	Palladium	0,107	1,509	0,344	0,311
	Platinum	0,040	0,882	0,221	0,182
	Silver	0,024	0,399	0,290	0,082
Oilseeds					
	Soybean	0,023	0,456	0,250	0,094
	Soybean meal	0,080	1,387	0,279	0,286
	Soybean oil	-0,040	-0,788	0,246	-0,162
Softs					
	Cocoa	-0,022	-0,366	0,292	-0,075
	Coffee	-0,087	-1,295	0,326	-0,267
	Orange Juice	-0,080	-1,308	0,297	-0,269
	Sugar	-0,014	-0,219	0,300	-0,045

6.2 Summary of Realized Skewness

Table 4 presents the time-series characteristics of the Pearsons skewness coefficient for each commodity, the ranking instrument used to implement portfolio sorting of the skewness strategy. Time-series variation of individual commodity skewness is apparent when comparing the 25^{th} and 75^{th} percentile as the sign of monthly skewness coefficient changes across quartiles for all commodities except soybean oil. On average, energy and metals sector commodities tend to exhibit negative skewness, whereas grains and oilseed sectors tend to have positive skewness.

Next, the constituents of the extreme portfolios are examined where commodities with most negative skewness are bought and commodities with positive skewness are sold, according to the realized skewness of daily returns on the front future over the previous year. Figure 2 reports the frequency of commodities in the extreme Q1 (negative skewness) and Q5 (positive skewness) portfolios when sorted in accordance with daily return skewness. The graph shows the percentage of months each commodity enters either of the extreme portfolios. The most frequent commodities to enter Q1 belong to the metals sector as Gold, Platinum and Silver are added roughly 50% of the time in the sample. Most frequent commodities in the opposite end Q5 belong to the grains and oilseeds sector, where Corn, Wheat, Soybean meal and Soybean oil all have a relative frequency above 30%. The results are comparable to those of Fernandez-Perez et al (2018), who also find that metals tend to enter the lowest skewness quintile and agriculture commodities are among the most frequent in the positive skewness quintile.

Table 4: Summary statistics for Pearson skewness coefficient. The mean is the average of monthly skewness coefficients. 25th, median and 275th stand for percentiles for each quartile.

Commodity	Mean	25th	Median	75th
Gasoline	-0,248	-0,393	-0,203	0,016
Heating oil	-0,054	-0,243	-0,059	0,142
Light crude oil	-0,218	-0,542	-0,174	0,065
Natural gas	-0,068	-0,257	-0,084	0,203
Corn	0,072	-0,159	0,033	0,330
Oats	0,016	-0,249	-0,080	0,122
Rough rice	0,067	-0,077	0,049	0,260
Wheat	0,165	-0,010	0,168	0,363
Cotton2	-0,032	-0,190	-0,035	0,157
Lumber	0,105	-0,001	0,084	0,229
Feeder Cattle	-0,107	-0,171	-0,087	0,023
Lean Hogs	-0,069	-0,190	-0,060	0,035
Live Cattle	-0,071	-0,186	-0,051	0,099
Copper	-0,075	-0,281	-0,027	0,232
Gold	-0,035	-0,662	-0,200	0,354
Palladium	-0,267	-0,529	-0,309	0,022
Platinum	-0,222	-0,510	-0,254	0,055
Silver	-0,454	-1,029	-0,307	0,030
Soybean	-0,063	-0,211	-0,041	0,099
Soybean meal	0,130	-0,140	0,073	0,351
Soybean oil	0,214	0,011	0,143	0,403
Cocoa	-0,108	-0,380	-0,018	0,197
Coffee	0,025	-0,186	0,019	0,301
Orange Juice	0,071	-0,237	0,026	0,250
Sugar	-0,070	-0,238	-0,038	0,134

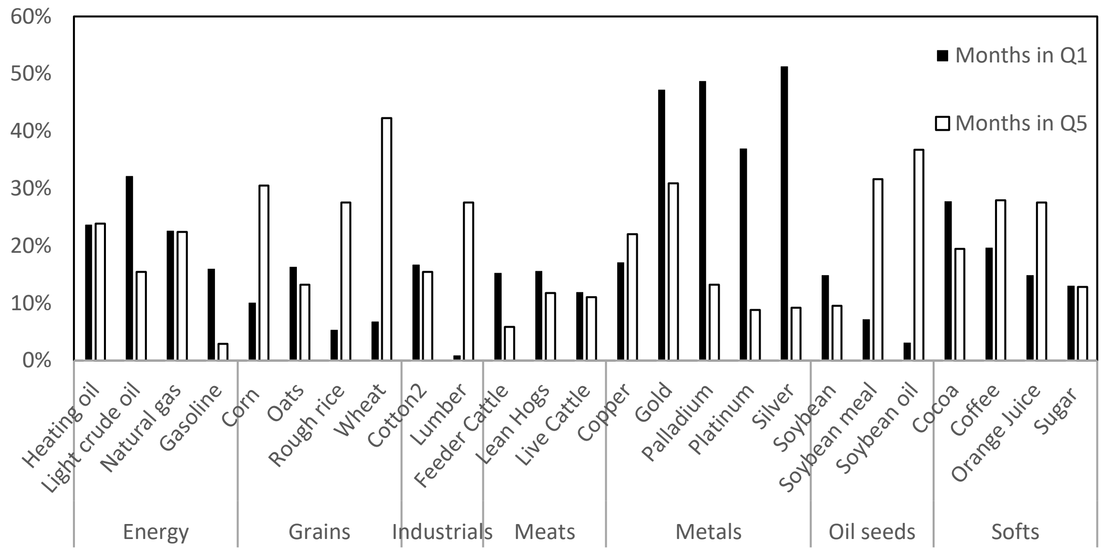


Figure 2: Frequency of commodities in Q1 and Q5

6.3 Descriptive Statistics for Spot Premia by Factors

Table 5 presents the descriptive statistics of the monthly returns for the skewness sorted quantiles, long-short Skew strategy and control factors. The results for the skewness sorted portfolios follow largely the results of those reported by Fernandez-Perez et al (2018), who find that the returns of the skewness strategy are largely driven by the extreme positive skewness quintile Q5. The same result is replicated here where Q5 delivers a highly significant (p-value less than 1%) negative monthly return of -90 basis points (-10,8 annualized). The main difference with the results of Fernandez-Perez et al (2018) is that the returns of the skewness quintiles do not decrease in monotonic fashion when moving from Q1 to Q5. In this study, Q3 is found to deliver a marginally significant negative return -50 basis points per month (-6% annualized). A similar result is found when the 1-month ahead of maturity roll method is used, albeit the results are not as significant. The results for the alternative return based on the later roll are reported on the 3rd table in the Appendix. The likely reason is that prior to the end of 2006, the sample consists of only 24 commodities and the middle quintile contains only 4, until RBOB gasoline began trading in 2006. Thus the poor results of Q3 could be driven by a higher concentration or lack of diversification relative to other quintiles.

Table 5: Summary statistics for monthly spot premia of Skew quintiles and controls. The mean is the average monthly excess return. STD is the standard deviation of monthly returns. T-stat represents the test statistic against the hypothesis that mean return equals zero. Sharpe represents risk-adjusted returns and is calculated by dividing annualized mean with annualized standard deviation. Q1-Q5 is the Skew strategy. EW is an equally weighted portfolio of all commodities. Carry represents a strategy that buys the most backwardated quintile and shorts the most contangoed quintile. Basis buys commodities with a below-median basis and shorts the opposite. Mom represents a strategy that buys recent winners and sells losers. The asterisk *,**,*** represent significance at the 10, 5,1% level respectively.

Skew quantiles					
	Q1	Q2	Q3	Q4	Q5
Mean	0,002	0,000	-0,005*	-0,001	-0,009***
STD	0,052	0,048	0,049	0,048	0,049
Tstat	0,641	-0,066	-1,722	-0,424	-3,016
Sharpe	0,135	-0,014	-0,362	-0,089	-0,635

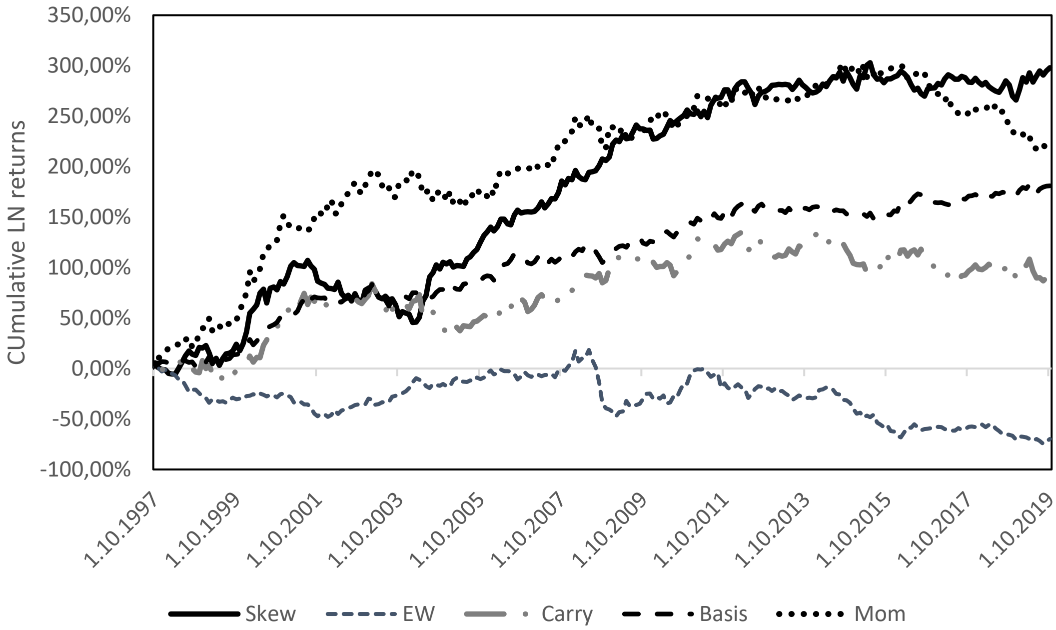
Strategies & Factors					
	Q1-Q5	EW	Carry	Basis	Mom
Mean	0,011***	-0,003	0,003	0,007***	0,008**
STD	0,056	0,052	0,054	0,034	0,063
Tstat	3,202	0,641	1,039	3,255	2,114
Sharpe	0,674	-0,237	0,219	0,685	0,445

The descriptive statistics for the long-short factors and the skewness strategy (Q1-Q5) are also reported in table 5. The skewness strategy delivers a highly significant return of 1,1% per month (13,2% annualized) and yields a Sharpe ratio of 0,67. The results are comparable to those of Fernandez-Perez et al (2018) who find that the strategy delivered a mean excess return of 8% per year with a Sharpe of roughly 0,78. Firstly the difference in mean excess returns is largely due to the manner of reporting. Fernandez-Perez et al (2018) calculate the returns by dividing the returns of the long and short portfolio in half, to account for the full collateralization where half of the capital would be invested in risk-free interest. Using the same reporting technique, the returns of the skewness strategy employed in this study would stand at 6,8%. Therefore the returns reported here, while still highly significant, are worse than those achieved previously looking at both mean annual excess return and Sharpe ratio. Figure 3 plots the cumulative logarithmic returns of the skewness strategy and the reason for slightly worse results seem to be the more stagnant returns the strategy has delivered since 2014.

The returns for the control factors are also largely expected. The momentum factor (Mom) delivered a significant 0,81 basis point monthly excess return (9,7% annualized) and the EW commodity future factor yielded a negative monthly return, though it was not statistically significant. The returns for the Carry factor, on the other hand, are not reflective of the results achieved for instance by Bakshi et al (2017). While the plot for carry quintiles is not reported here, the insignificant result of the Carry factor is largely driven by the poor performance of the most backwardated quintile (downward sloping futures curve) which the Carry factor buys. The results seem to be a product of the 2-month ahead of maturity roll, as the Carry factor delivers significant positive returns (9,8% annualized, 0,44 Sharpe) using the alternative 1-month roll method which is reported in the third table of the Appendix.

As a robustness check, an alternative basis based factor proposed by Szymanowska et al (2014) is applied as a control variable. The basis factor similarly ranks commodity futures according to basis and buys the commodities with below-median basis and sells commodities with an above-median basis. The basis factor delivered a highly significant monthly mean excess return of 70 basis points (7,9% annualized) and the highest Sharpe ratio of spot factors 0,685. Overall the Skew strategy performed very well in the sample period on the spot premium context, when compared to the traditional factors. The Skew strategy delivered the highest mean excess monthly return and the second-highest Sharpe ratio.

Figure 3: Cumulative LN spot returns by factors from 03/1997 – 10/2019.



6.4 Descriptive statistics for Term Premia Factors

For the term premia, descriptive statistics are presented in table 6. The term premia tend to be much smaller than the spot premia, as in Szymanowska et al (2014). However, the spreading returns are highly significant for numerous portfolios. The LowSkew portfolio yielded significant monthly excess spread returns for all different maturities (marginally significant for r^{spr3}). For example, on the r^{spr2} series the LowSkew yielded a highly significant monthly excess return of 16 basis points (1,92% annualized), and the average LowSkew strategy yielded a highly significant monthly excess return of 27 basis points (3,26% annualized). The HighSkew portfolio delivered highly significant excess returns for 2 out of 3 spread return series and the returns were not significant in the farthest maturity series r^{spr4}. Similarly, the average HighSkew delivered a highly significant monthly excess return of 19 basis points (2,29% annualized). On the term premia context, the LowSkew portfolios tend to deliver more significant results than the HighSkew, in contrast to the spot premia setting where the underperformance of positively skewed commodity futures were the most significant.

The Lterm (or low basis as in Szymanowksa et al 2014) portfolio delivers highly significant term premia across all maturities. For the average Lterm factor, the monthly excess returns stand at 34 basis points (4,1% annualized). On the other hand, the H-term basis factor delivers much weaker results as found in previous studies (Szymanowska et al 2014, Blocher et al 2018). The term premia of Hterm are statistically significant only for the most distant spreading return series, which also the main cause for the significance of the average H-term factor. The result are likely due to a more recent sample, and a slightly larger sample in terms of commodities. The cumulative logarithmic excess returns for term are plotted in figure 4 and the average H-term returns have stagnated since roughly 2009.

Figure 4: Cumulative LN term premia by factors 03/1997 – 10/2019. Plotted are the average returns by factor across different maturity spreads

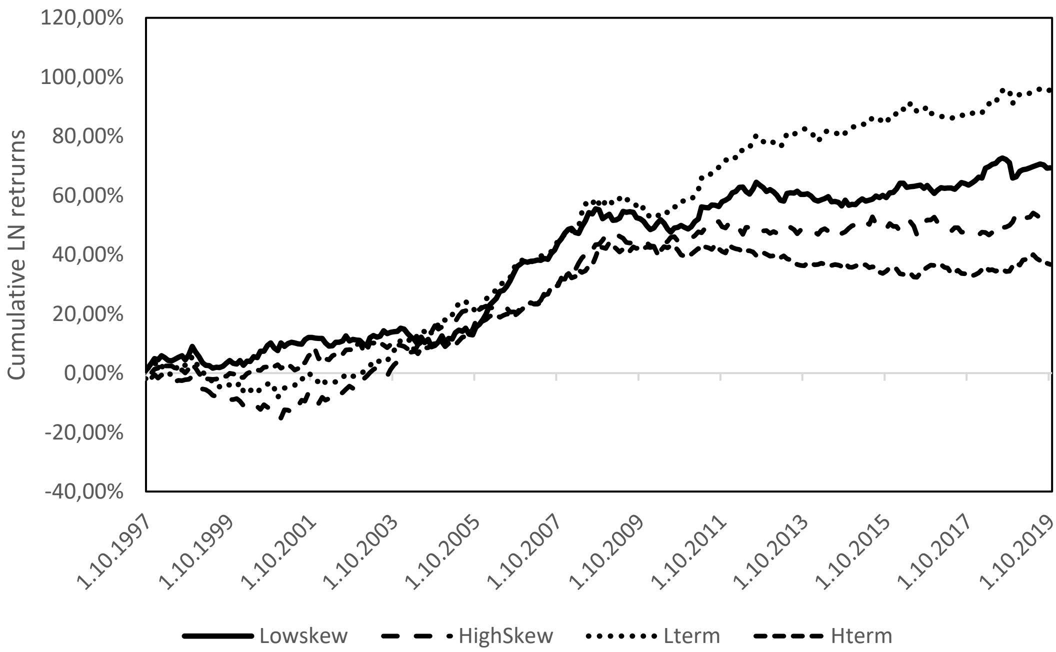


Table 6 Summary statistics for monthly term premia by Lskew, Hskew and controls. SPR2, SPR3 and SPR4 highlight calendar spreads going long on contracts that do not mature at least in 4, 6 and 8 months respectively, all short the spot return. Average resembles a strategy that buys the spreads of all maturities with equal weights and monthly rebalancing. LowSkew buys calendar spreads for commodities with below-median spot return skewness, HighSkew buys calendar spreads for commodities with skewness above the median. Lterm (Hterm) buy calendar spreads with the basis below (above) the median, measured using the front and second nearest contract. The mean is the average monthly excess return. STD is the standard deviation of monthly returns. T-stat represents the test statistic against the hypothesis that mean return equals zero. Sharpe represents risk-adjusted returns and is calculated by dividing annualized mean with annualized standard deviation.

LowSkew		r^{spr2}	r^{spr3}	r^{spr4}	Average
	Mean	0,002***	0,001*	0,005***	0,003***
	STD	0,006	0,014	0,026	0,012
	Tstat	4,643	1,732	3,190	3,761
	Sharpe	0,977	0,364	0,671	0,791
HighSkew		r^{spr2}	r^{spr3}	r^{spr4}	Average
	Mean	0,002***	0,002***	0,002	0,002***
	STD	0,006	0,014	0,025	0,011
	Tstat	4,659	2,991	1,034	2,832
	Sharpe	0,980	0,629	0,217	0,596
Lterm		r^{spr2}	r^{spr3}	r^{spr4}	Average
	Mean	0,003***	0,003***	0,004***	0,003***
	STD	0,006	0,016	0,026	0,013
	Tstat	8,685	2,891	2,707	4,519
	Sharpe	1,828	0,608	0,570	0,951
Hterm		r^{spr2}	r^{spr3}	r^{spr4}	Average
	Mean	0,000	0,001	0,003**	0,001***
	STD	0,006	0,012	0,024	0,010
	Tstat	0,096	1,252	2,141	2,249
	Sharpe	0,020	0,263	0,451	0,473

6.5 Time-series Regressions for Spot Premia

The results of the time-series regressions, on the spot premia context, are presented in table 7. Both individual skewness portfolios and the long-short strategy are regressed on the Bakshi et al (2017) 3-factor model, with EW, Carry and Momentum as the explanatory variables. Given how the Carry factor performed modestly in the sample an alternative model is also run where the Carry is replaced with the Basis factor proposed Szymanowska et al (2014). The key variable of interest is the intercept term (alpha) of the regressions, which is interpreted as risk-adjusted return independent of the control factors.

Both of the extreme skewness quintiles deliver significant monthly alpha at the 5 percent level or better when regressed on the Bakshi et al (2017) 3-factor model. However, it is worth keeping in mind that the average returns of the low skewness quintile Q1 failed to deliver significant average returns. All the individual portfolios also load significantly and positively on the EW factor, which means that the quintiles tend to fare better when the aggregate commodity market does well. The long-short skewness strategy yielded a monthly alpha of roughly 1% (12% annualized). Fernandez-Perez et al (2018) found an annual time-series alpha of 6,58% with a largely similar model which also added a hedging pressure factor. Using their return calculation method the skewness strategies annualized alpha in this thesis is 6,2% and significant at the 1%-level so the result is very similar. Also, the Skewness strategy only loads marginally on the Carry factor suggesting that the Bakshi et al (2017) has poor explanatory power which is also evident with 2,7% R-squared. As in Fernandez-Perez et al (2018), the asset pricing model is capable of explaining over half of the variance of the individual portfolios but much less for the long-short strategy. For robustness, the analysis is also carried out using the 1-month prior to maturity roll as in Fernandez-Perez et al (2018) and the results are reported in the third table in the Appendix. The results are found to be slightly more significant in economic terms and therefore the roll date seems to have little effect.

The alpha of the Skewness strategy, decreases both in economic and statistical magnitude when the Carry factor is replaced with the Basis factor, evident in the second panel of table 7. The monthly alpha of the skewness strategy decreases to roughly 80 basis points (9,6% annualized), but it is still significant at the 5% level. The skewness strategy also loads significantly on the basis factor. Numerous studies have found that strategies that sort commodities according to their basis tend to suffer from market-wide economic distress or during recessions (Bakshi et al 2017, Koijen et al 2018). Thus skewness is also partly exposed to the economic down-turn risk via basis and carry. The explanatory power of the model with basis factor is also higher to the one relative to carry but still stands at a modest 6,6%. The low R-squared together with the significant alpha suggests that the skewness strategy is still largely independent of the factors and contains novel information about expected returns. On the spot premia setting, the results support the selective hedging theory, where lottery preferences lead to negative expected returns for highly skewed assets.

Table 7: Time-series regressions for spot return. Dependent variables are listed on the top row, independent variables in the first column. Alpha denotes the intercept. Newey-West (1987) corrected t-statistics are on the parenthesis below the factor loadings. R^2 measures the explanatory power of the asset pricing model. Q1-Q5 is the Skew strategy.EW is an equally weighted portfolio of all commodities. Carry represents a strategy that buys the most backwardated quintile and shorts the most contangoed quintile. Basis buys commodities with a below-median basis and shorts the opposite. Mom represents a strategy that buys recent winners and sells losers. .The asterisk *,**,*** represent significance at the 10%, 5% ,1% level respectively.

Bakshi, Gao & Rossi (2017) 3-factor model						
	Q1	Q2	Q3	Q4	Q5	Q1 - Q5
Alpha	0,004**	0,002	-0,002	0,002	-0,006***	0,010***
	(2,029)	(1,075)	(1,188)	(1,002)	(-3,140)	(2,942)
EW	1,005***	0,998***	0,995***	1,031***	0,964***	0,041
	(15,847)	(20,330)	(18,420)	(16,113)	(16,553)	(0,384)
Carry	0,074	0,044	0,069	-0,086**	-0,084	0,157*
	(1,564)	(1,161)	(0,763)	(-2,502)	(-1,659)	(1,818)
Mom	0,029	0,029	-0,080	-0,009	0,015	0,014
	(0,532)	(0,894)	(0,771)	(-0,219)	(0,394)	(0,175)
R^2	0,554	0,614	0,583	0,643	0,540	0,027

Table 7 continued.

Model with the basis factor of Swymanowska et al (2014)						
	Q1	Q2	Q3	Q4	Q5	Q1 - Q5
Alpha	0,002	0,002	-0,002	0,002	-0,006***	0,008**
	(1,265)	(0,881)	(1,004)	(1,335)	(-2,681)	(2,244)
EW	0,979***	0,995***	1,010***	1,037***	0,973***	0,006
	(14,439)	(20,146)	(18,395)	(16,008)	(16,182)	0,054
Basis	0,326***	0,071	-0,117	-0,122**	-0,161**	0,487***
	(4,520)	(1,161)	(1,043)	(-1,903)	(-2,350)	(4,010)
Mom	-0,018	0,030	-0,027	-0,014	0,020	-0,037
	(-0,367)	(0,925)	(0,765)	(-0,355)	(0,475)	(-0,487)
R^2	0,586	0,614	0,583	0,641	0,543	0,066

6.6 Time-series Regressions for Term Premia

The results for term-premia time-series regressions are presented in table 8. Contrary to the spot premia, sorting on skewness does not yield significant alpha when regressed on Lterm and Hterm. LowSkew loads highly significantly on Lterm as well as Hterm, and the intercepts are not significant in economic or statistical terms in any of the maturity series. Furthermore, the explanatory power of the term-premia model is high ranging from 56,4 to 37% across different maturity spreads. Similar results hold for the Highskew portfolio. All in all sorting on skewness does not yield significant risk-adjusted returns as the returns of the skewness portfolios are largely spanned by the portfolios that are sorted in accordance with the basis. Therefore the results reinforce the finding of Szymanowska et al (2014), who found that other alternative term-premia strategies were spanned or priced by portfolios that were formed by sorting on the commodity futures basis.

Table 8 Time-series regressions for term premia. Dependent variables are listed on the top row, independent variables in the first column. SPR2, SPR3 and SPR4 highlight calendar spreads going long on contracts that do not mature at least in 4, 6 and 8 months respectively, all short the spot return. LowSkew buys calendar spreads for commodities with below-median spot return skewness, HighSkew buys calendar spreads for commodities with skewness above the median. Lterm (Hterm) buy calendar spreads with basis below (above) the median. Alpha denotes the intercept. Newey-West (1987) corrected t-statistics are on the parenthesis below the factor loadings. R^2 measures the explanatory power of the asset pricing model.

LowSkew	r^{spr2}	r^{spr3}	r^{spr4}
Alpha	0,000	0,000	0,001
	(-1,164)	(-0,555)	(1,017)
Lterm	0,559***	0,541***	0,646***
	(15,638)	(8,724)	(12,516)
Hterm	0,366***	0,318***	0,324***
	(8,716)	(4,792)	(5,899)
R^2	0,564	0,408	0,370
HighSkew	r^{spr2}	r^{spr3}	r^{spr4}
Alpha	0,000	0,001	-0,002
	(0,791)	(1,285)	(-1,260)
Lterm	0,427***	0,403***	0,330***
	(7,049)	(7,192)	(6,258)
Hterm	0,617***	0,612***	0,598***
	(10,454)	(9,277)	(9,163)
R^2	0,413	0,422	0,315

7 CONCLUSION

The main purpose of this thesis is to investigate the performance of investment strategies that use realized return skewness as a sorting instrument on commodity futures. The strategy buys commodity futures with low skewness and sells commodity futures with high realized return skewness. The strategy is motivated by selective hedging and preference for skewness, where hedgers excessively sell commodity futures with negative realized skewness and sell less or even buy positively skewed commodity futures. Consequently, positively skewed commodity futures become overpriced and have low expected returns while the opposite holds for negative skewness (Stulz 1996, Gilbert et al 2006, Fernandez-Perez et al 2018).

In addition, the predictive value of the skewness strategy is examined for the recently proposed decomposition of commodity futures risk premia by Szymanowska et al (2014). The spot premia skewness strategy only trades the front contract, where the lowest (highest) realized skewness quintile is bought (sold). The spot premia strategy is implemented in a similar manner as in the original study by Fernandez-Perez et al (2018), with the only differences being the sample used and a different rolling scheme for futures return calculations. In this thesis, all return indices roll two months prior to maturity month to avoid analysis based on thinly traded prices (as in Szymanowska et al 2014 among others). The term premia strategies buy calendar spreads on two skewness portfolios per maturity series Lowskew (Highskew) which buys spreads on futures with below (above) median skewness. Put differently the strategies enter into short positions in the front contracts and long positions in distant maturity contracts. To my knowledge, the predictive power of realized skewness over commodity futures term premia has not been previously investigated in financial literature.

The spot skewness strategy delivered a positive and significant monthly excess return of 1,1% (13,2% annualized) and an alpha that ranged between roughly 80 basis points and 1% depending on control factors (9,8% to 12% annualized). The results of the skewness strategy are largely driven by the poor significant performance of the short leg, high realized skewness quintile. The results are largely comparable to the ones discovered earlier by Fernandez-Perez et al (2018) and support selective hedging and skewness or lottery preference theories. The performance of the strategy has slightly deteriorated since 2014, which could be due to the publication or learning effect found by McLean & Pontiff (2016), where return predictability diminishes following the publication of results.

On the term premia setting the skewness, the signal is subsumed by the basis factors proposed by Szymanowska et al (2014). Sorting on skewness leads to an average monthly excess return of 27 basis points (3,26% annualized) for low skewness portfolios and 19 basis points (2,26% annualized) for high skewness quantiles. Once the returns of the high and low term-structure portfolios are controlled for the risk-adjusted returns of the skewness-portfolios are indistinguishable from zero.

As pointed out by Fernandez-Perez et al (2018) a possible further research topic in this area could be to investigate diversified skewness or lottery-based strategies across asset classes. Also, potential downside risk of the skewness strategy in the spot premia setting could warrant more specific investigation for instance by utilizing the downside beta model of Lettau, Maggiori & Weber (2013) as highly skewed assets can act as insurance as suggested by Barinov (2018) among others. Finally, the selective hedging hypothesis could also be more formally investigated similarly as hedging pressure was by Kang, Rouwenhorst & Tang (2020). The models and theories reviewed in this thesis suggest that the hedgers desire positive skewness and speculators provide the needed liquidity. A more formal analysis where one could examine how different investors adjust their positions following changes in the skewness of single commodities or aggregate commodity market skewness could be of interest.

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Appendices

Table 9: Summary statistics for excess returns, rolling 1-month ahead of maturity. The mean is the average annualized excess return. T-stat represents the test statistic against the hypothesis that the mean return equals zero. Std is an annualized standard deviation of excess returns. Sharpe represents risk-adjusted returns and is calculated by dividing annualized mean with annualized standard deviation. The asterisk *,**,*** represent significance at the 10, 5,1% level respectively.

Sector	Commodity	Mean	T-stat	Std	Sharpe
Energy					
	Gasoline	0,000	0,003	0,322	0,001
	Heating oil	0,032	0,511	0,307	0,105
	Light crude oil (WTI)	0,013	0,198	0,326	0,041
	Natural gas	-0,224**	-2,235	0,487	-0,460
Grains					
	Corn	-0,095*	-1,676	0,274	-0,345
	Oats	-0,006	-0,090	0,325	-0,018
	Rough rice	-0,114**	-2,225	0,248	-0,458
	Wheat	-0,142**	-2,300	0,300	-0,474
Industrials					
	Cotton2	-0,077	-1,347	0,278	-0,277
	Lumber	-0,091	-1,429	0,309	-0,294
Meats					
	Feeder Cattle	0,011	0,351	0,155	0,072
	Lean Hogs	-0,083	-1,405	0,289	-0,289
	Live Cattle	0,004	0,137	0,147	0,028
Metals					
	Copper	0,032	0,580	0,265	0,119
	Gold	0,030	0,912	0,162	0,188
	Palladium	0,099	1,384	0,346	0,285
	Platinum	0,036	0,800	0,221	0,165
	Silver	0,021	0,351	0,290	0,072
Oilseeds					
	Soybean	0,043	0,830	0,250	0,171
	Soybean meal	0,119**	2,029	0,284	0,418
	Soybean oil	-0,046	-0,897	0,248	-0,185
Softs					
	Cocoa	0,008	0,121	0,302	0,025
	Coffee	-0,072	-1,052	0,334	-0,217
	Orange Juice	-0,063	-0,993	0,306	-0,204
	Sugar	-0,029	-0,447	0,310	-0,092

Table 10: Excess returns (long-only) of farther maturity series for each commodity. N2, N3 and N4 are series that do not mature 4, 6 or 8 months from the present.

	N2				N3				N4			
Commodity	Mean	T-stat	Std	Sharpe	Mean	T-stat	Std	Sharpe	Mean	T-stat	Std	Sharpe
Gasoline	0,018	0,20	0,333	0,055	0,023	0,27	0,313	0,072	0,002	0,25	0,084	0,067
Heating oil	0,051	0,87	0,286	0,180	0,063	1,13	0,270	0,233	0,006	1,38	0,073	0,284
Light crude oil (WTI)	0,064	1,02	0,304	0,210	0,089	1,54	0,280	0,318	0,008*	1,87	0,075	0,384
Natural gas	-0,168**	-2,05	0,398	-0,422	-0,111	-1,61	0,336	-0,331	-0,005	-0,99	0,085	-0,203
Corn	-0,066	-1,25	0,258	-0,258	-0,057	-1,15	0,243	-0,236	-0,004	-1,01	0,066	-0,208
Oats	-0,016	-0,28	0,277	-0,057	-0,030	-0,58	0,253	-0,120				
Rough rice	-0,076*	-1,68	0,221	-0,346	-0,051	-1,18	0,208	-0,243				
Wheat	-0,105*	-1,83	0,280	-0,376	-0,077	-1,43	0,264	-0,294	-0,006	-1,32	0,071	-0,271
Cotton2	-0,052	-1,00	0,252	-0,206	-0,038	-0,78	0,237	-0,161	-0,003	-0,88	0,062	-0,181
Lumber	-0,050	-0,99	0,246	-0,204	-0,036	-0,81	0,214	-0,168				
Feeder Cattle	0,043	1,53	0,137	0,315	0,047*	1,78	0,128	0,367				
Lean Hogs	-0,004	-0,09	0,215	-0,019	0,017	0,49	0,173	0,100	0,040***	4,54	0,147	0,935
Live Cattle	0,024	0,94	0,123	0,193	0,019	0,89	0,106	0,182	0,002	1,21	0,028	0,250
Copper	0,048	0,91	0,257	0,188	0,052	1,01	0,251	0,208	0,005	1,08	0,071	0,222
Gold	0,032	0,97	0,162	0,200	0,033	0,98	0,162	0,202	0,003	0,98	0,047	0,202
Palladium	0,121*	1,84	0,318	0,380								
Platinum	0,046	1,02	0,219	0,211								
Silver	0,028	0,47	0,289	0,096	0,029	0,49	0,288	0,101	0,003	0,55	0,083	0,114
Soybean	0,028	0,57	0,241	0,118	0,028	0,60	0,230	0,123	0,002	0,54	0,063	0,110
Soybean meal	0,061	1,11	0,268	0,228	0,059	1,14	0,251	0,235	0,004	1,09	0,068	0,225
Soybean oil	-0,035	-0,71	0,240	-0,145	-0,021	-0,44	0,234	-0,091	-0,001	-0,30	0,065	-0,061
Cocoa	-0,011	-0,19	0,283	-0,038	-0,008	-0,15	0,274	-0,030	0,000	-0,10	0,077	-0,020
Coffee	-0,082	-1,29	0,308	-0,265	-0,076	-1,27	0,292	-0,261	-0,006	-1,19	0,080	-0,245
Orange Juice	-0,074	-1,28	0,280	-0,263	-0,073	-1,36	0,263	-0,279	-0,006	-1,34	0,073	-0,275
Sugar	-0,006	-0,11	0,266	-0,023	0,002	0,04	0,238	0,008	0,001	0,24	0,062	0,049

Table 11 Results for spot premia, rolling 1 month ahead of maturity. Panel A reports monthly summary statistics for the Skew quintiles. Panel B reports monthly summary statistics for the Skewness strategy and controls. Panel C reports time-series regressions, where the Skew quintiles and long-short strategy (Q1-Q5) strategy is regressed on the Bakshi et al (2017) 3-factor model.

Panel A					
Skew quantiles					
	Q1	Q2	Q3	Q4	Q5
Mean	0,002	0,001	-0,004	-0,002	-0,009
STD	0,051	0,050	0,051	0,049	0,047
Tstat	0,710	0,276	-1,225	-0,715	-3,174
Sharpe	0,149	0,058	-0,258	-0,151	-0,668

Panel B				
Strategies & Factors				
	Q1-Q1	EW	Carry	Mom
Mean	0,011***	-0,002	0,008**	0,008*
STD	0,058	0,037	0,057	0,067
Tstat	3,219	-1,056	2,307	1,955
Sharpe	0,677	-0,222	0,486	0,411

Panel C						
Bakshi, Gao & Rossi (2017) 3-factor model						
	Q1	Q2	Q3	Q4	Q5	Q1 - Q5
Alpha	0,002	0,000	-0,005	-0,003	-0,010***	0,012***
	(0,608)	(0,079)	(0,072)	(-0,723)	(-3,443)	(3,057)
EW	0,026	0,070	0,036	0,028	0,151	-0,125
	(0,232)	(0,847)	(0,423)	(0,205)	(1,347)	(-1,635)
Carry	0,055	0,049	0,111	0,071	0,097	-0,042
	(0,983)	(0,819)	(0,797)	(1,429)	(1,717)	(-0,693)
Mom	-0,020	0,048	-0,008	-0,008	0,009	-0,029
	(-0,422)	(0,953)	(1,154)	(-0,197)	(0,191)	(-0,517)
R^2	-0,008	0,003	0,005	-0,004	0,022	0,012