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The challenges of oil investing: Contango and the financialization of commodities[☆]

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ABSTRACT

The ability of oil investment vehicles to perfectly track spot oil has always been challenging; however, recently many vehicles have underperformed spot oil. We study the behavior of oil futures and exchange-traded products that invest in oil futures to document and understand the source of this tracking error. The primary reason why oil investment vehicles have underperformed spot oil is an increase in contango in oil futures markets that we find might be related to investment crowding and the financialization of commodity markets. We show that from 2006 to 2017, oil futures investing underperformed spot oil and the market was in contango most of the time. Proxies for crowding, such as the concentration of major oil investors and changes in assets under management and fund flows of major oil exchange-traded products, are associated with contango in the futures markets and the divergence between futures and spot returns. We also provide evidence of an impact of the financialization on oil futures prices.

1. Introduction

Commodity investing is very different than equity or bond market investing. For investing in oil to be liquid, an investor can choose either liquid futures contracts on crude oil, public companies in the oil or energy business, managed products such as oil exchange-traded products (ETPs), or mutual funds that typically invest in oil companies or oil futures.[1]

The benchmark that many investors use when measuring the performance of oil-investing vehicles is the performance of spot oil.[2] The challenge is that investing in spot oil is not practical. Thus, investors who purchase oil futures contracts incur the challenge that the returns of futures may differ from spot oil. Investors in oil companies face an even greater challenge in that the returns of oil companies may differ from the returns of spot oil for a host of reasons, including business exposures, internal oil hedging, stock market risk, and more.

Another challenge with oil investing is that as more investors trade futures on oil, this puts pressure on oil futures prices, which might cause futures returns in oil to deviate from the returns of spot oil and create a tracking error. We call this the challenge of crowding. Crowding may have been exacerbated by the financialization of commodity markets.[3] Commodities have become a separate asset class and several investment vehicles (e.g., ETFs) have been launched to

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[1] ETPs consist of exchange-traded funds (ETF), exchange-traded notes (ETN), exchange-traded commodities/currencies (ETC), and exchange-traded vehicles (ETV). ETFs are the largest and most common products. See Ben-David et al. (2017) for a survey of the ETF literature.

[2] Although ETPs do not claim to match the return of the spot commodity in their prospectuses, this is an implicit benchmark adopted by practitioners and investors. Moreover, some ETPs state in their prospectuses that they aim to track the daily price movements of spot oil. For example, the prospectus of the largest oil ETF, the United States Oil Fund (USO), states that USO is "an exchange-traded security designed to track the daily price movements of West Texas Intermediate light, sweet crude oil." Although the prospectus states that the USO's benchmark is the near month crude oil futures contract traded on the NYMEX, data providers such as Morningstar list the West Texas Intermediate light, sweet crude oil as the primary benchmark of USO.

[3] Crowding and financialization are related concepts because both may induce prices to drift away from fundamentals. The difference is that crowding is a more general concept referring to a supply and demand imbalance related to underlying liquidity, not necessarily related to flows of investment funds.

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allow investors to get exposure to this asset class.[4] According to the Investment Company Institute, the total net assets managed by commodity ETFs grew from $1.3 billion in 2004 to as high as $120 billion in 2012. In 2004 there was only one commodity ETF and in 2018 there were 91 commodity ETFs. As explained by Singleton (2014), the flows of funds into the commodity market may result in prices being pushed away from fundamentals due to investment frictions that limit arbitrage activity.

Irwin and Sanders (2011) and Boyd et al. (2018) review the literature on the financialization of commodity markets and conclude that there is little evidence that commodity index investing leads to price distortions in the futures and spot commodity markets.[5] The findings related to the oil market are more nuanced. Some papers provide evidence that the financialization affects oil futures prices. Singleton (2014) finds that a 13-week measure of change in index-fund holdings computed from the Commitments of Traders Supplemental reports predicts oil futures returns contracts from 2006 to 2010. Stoll and Whaley (2010) find that for oil futures, different from the other commodity futures, there is evidence of an impact of commodity index investment rolls on futures prices.[6] Other papers argue for the opposite view. Hamilton and Wu (2015) find that Singleton's (2014) finding breaks down out of sample. Bessembinder et al. (2016) examine the impact of roll trades by the largest oil ETF (USO) and find that preannouncing the roll dates attracts liquidity suppliers; hence, these trades have limited price impact. Büyükşahin and Harris (2011) use proprietary CFTC data on daily positions of different types of traders in the oil futures market and find little evidence that hedge funds and other non-commercial position changes predict futures price changes. Sanders and Irwin (2011) conduct causality tests on various commodity markets including oil and find no evidence of a link between index trader positions and futures prices.

In this paper we contribute to this debate by uncovering new evidence that supports the idea that crowding and financialization may have distorted prices in the futures markets. Our empirical analysis can be summarized as follows. First, we study the behavior of oil futures, as well as ETPs that invest in oil futures and oil companies, to document the source of this tracking error. We find that tracking error has always been present and eliminating it does not seem possible, as confirmed by Chincarini (2020). We also document that, from 1994 to 2005, oil futures investing outperformed spot oil, while from 2006 to 2017, oil futures investing underperformed spot oil. Interestingly, during the first sample period, the market was, most of the time, in backwardation and shifted to contango (up to 82% of the time) during the most recent sample period.[7] We also decompose futures returns into spot and roll components. The spot component represents the change in price for a given futures contract, whereas the roll component represents the percentage return from rolling the futures contract if the futures curve remains constant. The magnitude and the sign of the roll return depends on whether the market is in contango or backwardation. We find that a significant portion of futures returns comes from the roll return and that this (and the associated contango) is the driver of the negative return in futures investment strategies and ETPs that invest in oil futures.

Next, we attempt to measure whether the crowding and financialization of the oil investment space is related to contango and to the difference between spot and futures returns. Crowding has been shown to affect several other markets, especially equities, but so far no direct examination of crowding has been done in the commodity markets.[8] We run predictive regressions of futures returns, the difference between spot and futures returns, and contango on crowding variables and control variables using weekly and daily data. The crowding variables include aggregate positions from the Commitments of Traders (COT) data released by the CFTC and data on oil ETPs. For the weekly analysis, given the large number of crowding variables, we extract the first two principal components from these variables. We find that the first principal component is negatively associated with the following week's difference between futures and spot returns and positively associated with the following week's contango. Consistent with the existing literature, we find weak results when we predict futures returns instead of the difference between futures and spot returns.

At the daily frequency, we have only ETPs and futures volume data. We find that fund flows and the changes in daily assets under management of major oil ETP companies are associated with lower subsequent returns in the difference between futures and spot. We also find that past volume is positively associated with contango. We also estimate a vector autoregressive (VAR) model. Granger causality tests provide further evidence that crowding leads to an increase in contango and the divergence between futures and spot returns. Oil ETPs have experienced a tremendous growth, but they appear to be victims of their own success. The increase in assets under management contributes to the contango, which is a drag on their performance when compared with spot oil.

One concern of studies that examine the impact of the financialization of commodities on futures prices is endogeneity. In the above analyses, we mitigate this concern by lagging the independent variables. To further address this concern, we identify changes in demand that are not based on information about futures price movements.[9] Our identification strategy is to focus on the dates when a futures contract was first acquired by some of the main oil ETFs. These dates correspond to non-fundamental changes in demand driven by ETFs trading. Indeed, these changes are driven by the expiration cycle of the futures rather than by price expectations of ETF investors. We find evidence of an impact of financial passive investments on futures prices as evidenced by the volatility of the futures returns and the correlation between the returns of the front futures contract and the back contracts are higher during these dates.[10]

Finally, to provide further support for the impact of financialization on the futures markets, we run a set of heterogeneity tests. First, we investigate whether oil recently has been more exposed to equity factors, such as the Fama–French factors. Consistent with an increase in dependence between commodities and other traditional asset classes

[4] The main argument is that adding commodities to your portfolio provides hedging properties against inflation and improves the asset allocation, given the low correlation with other asset classes (e.g., Gorton and Rohwenhorst (2006) and Plante and Roberge (2007)).

[5] Another recent paper by Chari and Christiano (2017) reaches the same conclusion. There are also papers (e.g., Brunetti and Büyükşahin (2009), and Brunetti et al. (2016)) that argue for positive effects of financialization in terms of reduction in spot price volatility.

[6] Nguyen et al. (2020) also provide some recent evidence of increasing financialization for energy commodity futures.

[7] Contango is the term used to describe an upward-sloping futures curve where the current futures price of an asset (as quoted in the futures market) is higher than the current spot price of the underlying asset and longer-dated futures prices are higher than near-dated futures prices. Backwardation is the term used to describe a downward-sloping futures curve where the current futures price of an asset is lower than the current spot price of the underlying asset and longer-dated futures prices are lower than near-dated futures prices.

[8] For studies focusing on the equity market see, among others, Chincarini (1998, 2012), Cahan and Luo (2013), Anton and Polk (2014), Ibbotson and Idzorek (2014), Menkveld (2014), Chue (2015), Blitz (2017), Zhong et al. (2017), Bruno et al. (2018), Chincarini (2017), Kinlaw et al. (2018), Baltas (2019), Brown et al. (2019), and Marks and Shang (2019).

[9] Henderson et al. (2015) also address the endogeneity problem by focusing on the issuance of commodity-linked notes.

[10] Correlation has been used as a measure of crowding in several papers (e.g., Cahan and Luo (2013), Baltas (2019), and Lou and Polk (2020)). Correlation has also been used to capture the effects of ETFs on stock returns (e.g., Agarwal et al. (2018) and Da and Shive (2018)) and as evidence that financialization increases links among different commodities and other asset classes (see Tang and Xiong (2012) and Zhang et al. (2017)).

due to financialization, we document that the exposure of the oil market to the equity market was close to zero from 1994 to 2005 and became positive and significant in the most recent sample period. Second, we investigate whether oil futures returns are impacted by important scheduled macroeconomic news. We find that before 2006, there was almost no significant impact of macro news on futures returns (consistent with Kilian and Vega (2011)), whereas in the sample after the financial crisis, we find that 6 out of 21 economic announcements significantly impacted futures returns.[11] This result is consistent with the finding that the oil futures market is behaving more similar to the equity market. Lastly, consistent with financialization of commodities and crowding, we find that the correlation between the futures' returns with different expirations increased in the most recent period. For example, the correlation between the front contract and the furthest back contract increased from 0.82 in the sample until 2006 to 0.93 in the sample after the financial crisis.

We differ from the previous literature on the financialization of the commodity markets in three main ways. First, we consider the effect of financialization not only on futures returns but also on contango and the difference between futures and spot returns. Other papers (e.g., Erb and Harvey (2006)) consider a futures return decomposition in a spot component driven by the underlying commodity price and a roll component driven by the futures term structure, but they do not relate them to financialization. It is important to examine the effect of commodity investing and crowding on the different components of futures returns. Erb and Harvey (2006) find that roll returns explain 91.6% of cross-sectional variation of commodity futures' excess returns. Szymanowska et al. (2014) identify two types of risk premia in commodity futures returns: spot and term premia. The spot premium is related to the risk in the underlying commodity and the term premium is related to the slope of the term structure of futures prices and hence, it is closely related to the contango measure. Given that commodity investing and crowding are unlikely to reflect private information about the commodity price, then they are more likely to affect the term premium rather than the spot premium. Second, we measure the impact of financialization and crowding by combining data on oil-focused ETP flows and assets with the COT data on different traders in the futures markets. Third, we use changes in holdings of futures in the ETFs and intraday data to provide a more precise identification of the impact of financialization of commodity futures prices.

In this paper we focus on oil for several reasons. First, it is one of the most important commodities with the largest weight in the S&P GSCI commodity index.[12] Second, oil ETFs have been some of the most actively traded commodity ETFs (for example, as of August 2018, the average daily volume of USO is more than $300 million) and index investing of crude oil futures accounts for 31.7%, the highest proportion, of all commodity index investing in 2008 (see Table VII in Stoll and Whaley (2010)). Finally, as mentioned previously, the debate about the impact of oil index investing on oil futures prices is still open and there is the need for more research to examine more data (e.g., ETF data) and focus on the impact on contango and the difference between futures and spot returns.

This paper is also related to the recent ETF literature that investigates the impact of ETF trading on the underlying assets in the ETF portfolio. Da and Shive (2018) show that ETF arbitrage activity contributes to comovement in equity returns. Agarwal et al. (2018) document that common ETF ownership at the stock-pair level is associated with greater commonality. Baltussen et al. (2019) show that the serial correlation in equity returns becomes negative after the introduction of ETFs. Ben-David et al. (2018) provide evidence that ETFs increase the nonfundamental volatility of the securities in their baskets. Therefore, there is evidence from the equity market that ETFs transmit non-fundamental shocks to the underlying securities in the portfolio and this evidence is also supported by theoretical models (e.g., Bhattacharya and O'Hara (2018)). The results in this paper provide support for a similar transmission in the commodity markets.

The paper is organized as follows: Section 2 discusses the challenges of oil investing with respect to tracking spot oil, as well as how it is related to contango; Section 3 presents evidence on the effects of crowding and financialization on futures returns and contango; and Section 4 concludes the paper.

2. Challenge 1: Contango and tracking error

The first challenge in oil investing is that the perceived benchmark for oil investors is the spot oil return. However, investing in oil futures or oil companies is not the same, and this causes problems in terms of perception. In fact, a strategy of investing in individual futures contracts does not replicate the returns of spot oil. Similarly, a strategy of investing in oil companies does not replicate the returns of spot oil. All of the ETPs that invest in oil have a tracking error with spot oil, which has led to complaints and criticisms in the press (Blas (2008), Burton and Karsh (2009), Constable (2016), and Eisen and Leslie (2016)).

In fact, a simple spot oil benchmark is not a realistic benchmark.[13] The reason for this is that oil cannot be owned without significant costs. To directly invest in spot oil, an investor would have to buy physical oil and store it somewhere.[14]

Storage of oil is estimated to cost anywhere between $0.20 and $1.20 per barrel per month.[15] In March of 2015, the CME introduced the LOOP futures contract, which trades oil storage. The contract gives the buyer the right to store 1,000 barrels of crude oil at the LOOP Clovelly Hub in South Louisiana and provides us with some data on the market cost of storage per barrel. Over the period March 2015 to February 2017, storage prices averaged 42 cents per barrel. This is not a trivial amount. For example, when oil trades at $36 per barrel, it is equivalent to a cost of 1.17% per month. Thus, a more relevant index for oil is one that subtracts storage costs from the spot price of oil. For example, we can use data on the LOOP futures contracts to construct a more realistic spot benchmark for the sample period starting in March 2015. Fig. 1 shows the historical storage prices as determined by the near-term LOOP contract and also the adjusted spot

[11] Interestingly, when we focus on an oil market-specific news (the EIA weekly crude oil inventory reports), that has been shown to have a significant impact on the futures oil prices (e.g., Bu (2014)), we find that the magnitude of the coefficient that captures the impact of the news is reduced for the most recent sample in comparison with the sample before 2006.

[12] The combined weight of WTI and Brent crude oil is 41.6% as of January 2018 (see https://www.etfstrategy.com/sp-dow-jones-indices-announces-sp-gsci-composition-for-2018-49376/).

[13] Spot prices are still relevant. They are clearly important for producers and consumers of oil who have storage capability and use the futures market for hedging reasons. The spot prices are also relevant for arbitrageurs who try to profit on the spread between spot and futures prices. Spot prices also enter into inflation measures (e.g., CPI and PPI), and investors care about inflation. Finally, as highlighted earlier, the investment community and ETP providers often perceive the benchmark to be spot oil.

[14] For example, Cushing, Oklahoma, is a common place to store oil in the United States. Oil can also be stored on ships in the ocean, as well as salt dome caverns, large tanks above ground, small tanks above ground, and floating storage (listed in order of increasing storage costs). One can also think of reducing production as a form of storage, but this is also costly. Shutting down a well leads to loss of foregone revenue, but also further damage to the reservoir from the shutdown. The costs vary depending on the location and type of oil extraction.

[15] Deutsche Bank estimates that oil storage costs are roughly $0.40 per barrel per month and amounted to costs of 22% per annum between 1989 to 1994 (Brhanavan et al. (2007)). In 2008, analysts estimated oil storage costs on land between 40 and 70 cents per month per barrel and floating or ship storage costs as high as $1.60 per month per barrel (Blas (2008)). Goldman Sachs used a monthly cost of 0.80% for oil storage costs (Greely (2008)).

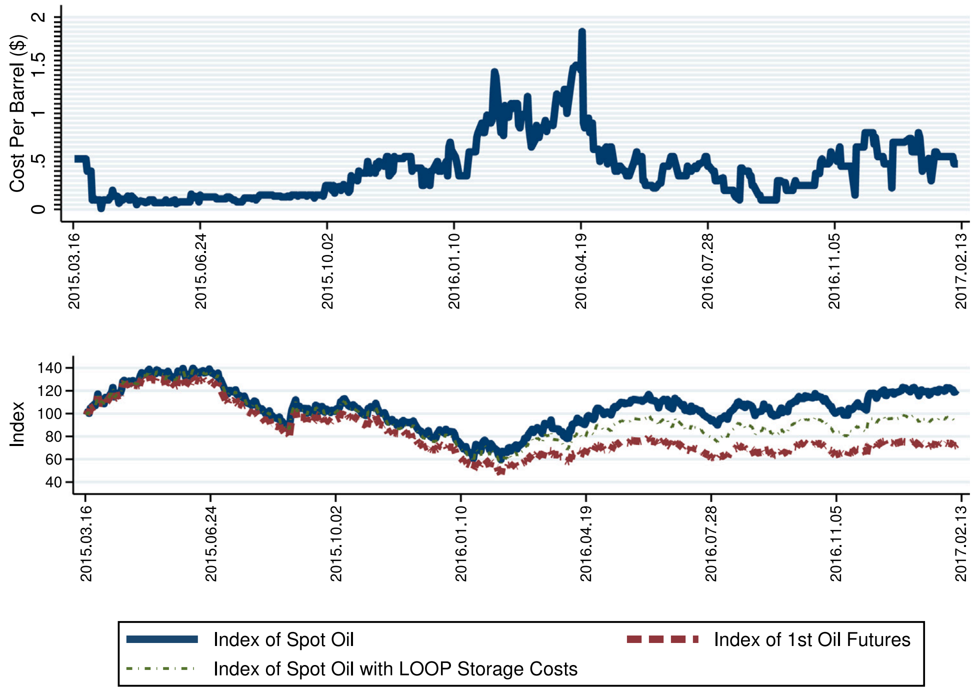

Fig. 1. LOOP Storage Costs and Spot Oil Adjusted for Storage Costs. The top figure shows the daily costs of storage of 1000 barrels of oil in dollars per barrel based on the nearest-term LOOP futures contract traded on the CME. The bottom figure shows an index of spot oil, spot oil adjusted for storage costs, and an index of rolling the nearest-term futures contract. All indices start at 100.

return of oil, along with the futures roll strategy. The storage prices reached a maximum of $1.85 per barrel and a minimum of $0.01 per barrel, with an average cost per barrel of 42 cents. One can see, that, although there is still tracking error between the near-term oil futures contract and spot oil, it is reduced by a large amount, when storage costs are properly accounted for.[16]

Despite the impracticability of a spot oil benchmark, it is still considered as a reference by practitioners and investors. This paper first analyzes the reasons for the divergence of spot oil from oil investing strategies and then tests whether financialization and crowding affect this divergence.

Oil futures began trading on the NYMEX (now CME) in 1983 (see Appendix A for a description of the data). From 1985 to 2017, the average daily volume on the first 51 contracts grew 15.01% on an annualized basis from 294,371 contracts to 25,860,034 (see Table 1). Average open interest has also increased by 12.76% on an annualized basis, from 50,283 contracts to 2,349,593 contracts.

This divergence in oil futures from the underlying spot oil can be seen in Fig. 2, which shows the growth of $100 from the beginning of 2006 to February 2017 for rolling the nearest-term futures contract, the 6-month futures contract, and the 12-month futures contract. All of the different futures contracts have tracking errors with spot oil, but the worst tracking error occurs with the first month (i.e., nearest-term or front) futures contract.

Table 1
The Growth in the Oil Futures Market.
Source: Bloomberg.

Year	Avg. Volume	Avg. Open Interest
1985	294,371	50,283
1990	1,381,780	268,773
1995	2,029,399	464,411
2000	3,149,263	600,463
2005	5,195,837	1,177,288
2010	14,123,448	1,321,122
2015	16,875,267	1,690,173
2017	25,860,034	2,349,593

Note: The table presents the average monthly volume and open interest averaged across 51 contracts in selected years.

Naturally, the fact that oil futures contracts do not perfectly mimic spot oil returns will affect any investment managers who attempt to track spot oil. In fact, their problem will be slightly larger, because they charge fees which will also reduce the net performance of the investment vehicles. In the ETP and mutual fund world, there are managers who invest in oil by buying futures contracts and those who invest in oil by buying oil company stocks. They are not free from this problem either. Fig. 3 shows the performance of the two largest oil ETPs (USO and OIL) that invest in futures, the two largest oil ETPs (XLE and VDE) that invest in oil companies, and the two largest mutual funds (VGENX and FSENX) that invest in oil companies.[17] Once again, one can see that the worst performers versus spot oil were the two ETPs that use futures, USO and OIL. Over the entire period, the total return of USO and OIL was −67.71% and −73.36%, respectively, compared with 20.72% for spot oil. The ETPs that invested in oil companies had the least tracking error over the entire period from

[16] The return of this more appropriate oil benchmark was calculated as

$$r_{t,t+k} = \left(\frac{S_{t+k}}{S_t} - 1\right) - \frac{u \cdot k}{30} \tag{1}$$

where u represents the monthly storage costs according to the near-term LOOP contract, k represents the days over which the return is computed, and a typical month is assumed to consist of 30 days. There is still a tracking error because storage costs are not the only costs involved; there are also insurance and transportation costs. Furthermore, although the daily traded LOOP storage value represents the costs for the month after expiration, this calculation is an approximate adjustment for storage costs. Obtaining actual storage costs is extremely difficult. Most private companies do not collect this information or will not give it out. Public agencies do not capture these data either. This problem was first highlighted in Chincarini et al. (2016).

[17] The largest are those with the most assets under management as of the beginning of 2018. None of the mutual funds invest solely in futures contracts.

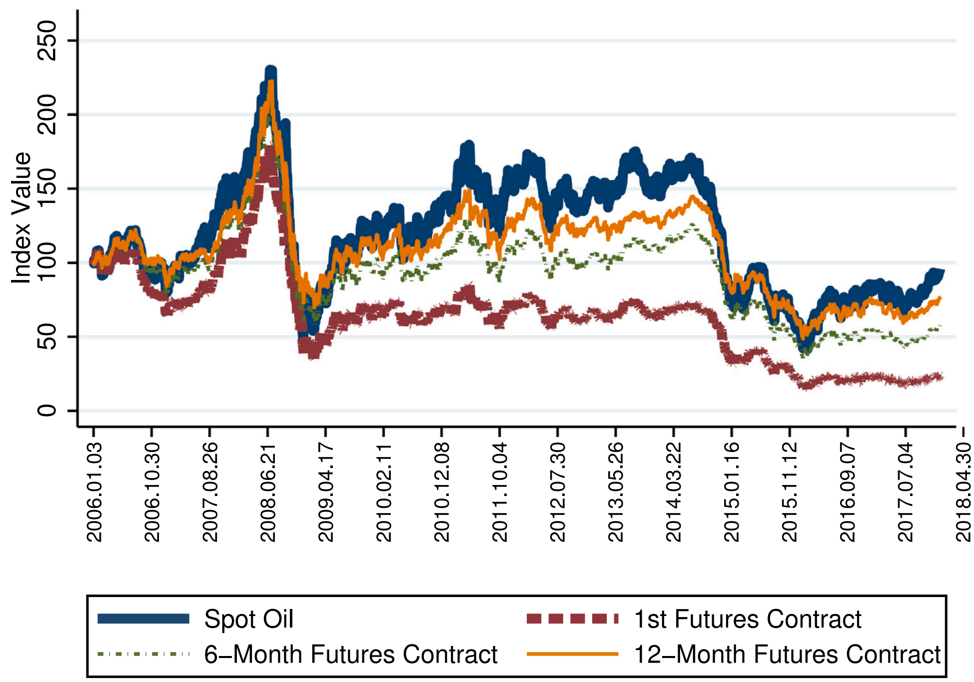

Fig. 2. Performance of Oil Futures and Spot Oil. This figure shows the cumulative returns of investing in spot oil and three rolling futures contracts; the 1-month, 6-month, and 12-month futures contracts. The strategy rolls futures on the expiration date of the front contract at closing futures prices. All indices start at 100.

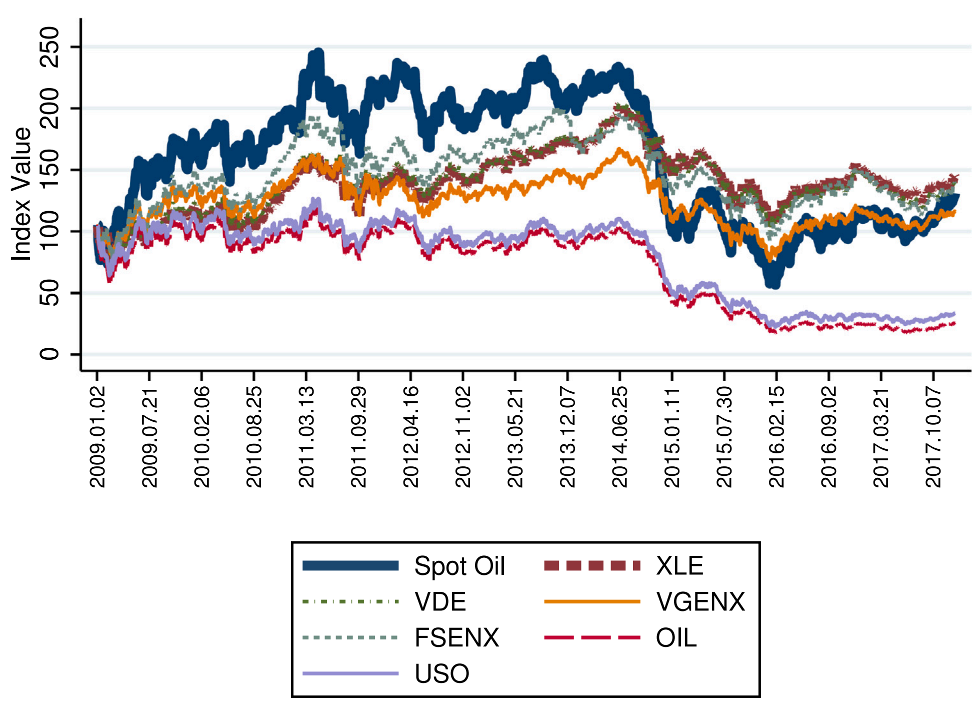

Fig. 3. Performance of the Largest Oil Investing ETPs and Mutual Funds. The figure shows the net-of-fee performance of different investment vehicles. The largest ETPs investing in oil futures are USO and OIL. The largest ETPs investing in oil companies are XLE and VDE. The largest mutual funds in investing in oil companies are FSENX and VGENX. All indices start at 100.

2009 to February 2017.[18] Over the entire period, the total returns of XLE and VDE were 46.16% and 42.44%, respectively, compared with 20.72% for spot oil. However, in the interim, even those ETPs had a poor tracking performance with spot oil. Tracking error was above 29% on an annualized basis for all ETPs and mutual funds investing in oil companies. Ultimately, the tracking error issue is a problem for all oil investment vehicles.

[18] We started in 2009, since many of the ETPs did not exist prior to 2009. The first oil investing ETP was USO, which started in March 2006.

Table 2
Summary Statistics about Contango and Backwardation in the Oil Market.

Strategy	Contango (%)							Avg. Volume
	Mean	Median	S.D.	Max	Min	Days	nobs	
Investment Period: 1994–December 2005								
Fut1Roll0	−2.43	−0.53	54	5.63	−24.11	42	3001	67,242
Fut2Roll0	−4.46	−2.28	15	0.95	−1.32	42	3001	43,821
Fut6Roll0	−5.62	−5.44	11	0.39	−0.59	31	3001	2,488
Fut12Roll0	−5.34	−5.34	9	0.22	−0.31	28	3001	640
Investment Period: 2006–February 10, 2017								
Fut1Roll0	2.10	0.36	16	1.99	−3.52	56	2797	298,998
Fut2Roll0	7.03	4.34	12	1.34	−0.53	82	2797	135,657
Fut6Roll0	5.10	4.59	8	0.54	−0.17	77	2797	14,461
Fut12Roll0	3.07	3.19	6	0.29	−0.11	74	2797	4,190

Note: The table presents various statistics with respect to the contango in the futures market. For each futures contract, the first number indicates the specific futures contract, either 1, 2, 6, or 12 depending on whether the nearest-term, second, sixth, or 12th contract is used. The second number represents the roll date. Thus, a "0" indicates the contract was theoretically rolled on the expiration date of the front contract. Mean represents the annualized mean daily contango in percentage terms for the particular contract and roll. Median represents the annualized median contango, S.D. represents the standard deviation of daily contango annualized by multiplying by $\sqrt{250}$ in percentage terms, and Max and Min represent the maximum and minimum annualized daily contango. Days represents the percentage of days that the market is in contango as opposed to backwardation. Nobs represents the number of daily observations used for the calculations, and Avg. Volume represents the average daily volume of the representative contracts. The calculation of contango is explained in Appendix D.

2.1. Contango and backwardation

Before studying in detail the characteristics of investing in the futures market, it is worthwhile to examine to what degree the market for oil futures is in backwardation or contango. Table 2 presents the statistics for the first, second, sixth, and 12th month futures contracts for two historical periods, 1994 to 2005 and 2006 to 2017, for the strategy of rolling the contracts at expiration.[19]

Over the first period, 1994 to 2005, the percentage of contango and backwardation has varied by contract. For the near-term futures contract, the market has been in contango 42% of the business trading days. The second futures contract has also been in contango 42% of the time, while the 6-month contract 31% of the time, and the 12-month contract for 28% of the time.[20] For those four contracts, the mean annualized contango has varied from −5.62% (i.e., backwardation) to −2.43%. These are annualized numbers. Thus, in the period 1994 to 2005, the oil futures markets were primarily in backwardation, which was stronger for longer-maturity contracts.

In the second period, from 2006 to 2017, the very nature of the oil futures market changed. The market switched from being primarily in backwardation to primarily in contango. For some particular contracts, the percentage of contango has been quite large. For example, for the 2-month futures contract rolled at expiration over the period 2006 to 2017, the market has been in contango 82% of the time, with an annualized measure of contango of 7.03%. This is extremely high and would present return challenges for investors rolling futures contracts and attempting to track a spot oil benchmark. Interestingly, the long-dated futures (e.g., 12-month futures) were in contango only 28% of days in the first sample compared to 74% in contango in the most recent sample. Therefore, there is no escape from contango even by investing in long-dated futures.

The recent contango has been such an issue for oil investors because it tends to reduce the returns to investing in oil futures and causes a larger tracking error with spot oil. There can also be tracking error when there is backwardation in the oil market. However, since this usually improves the returns of investing in futures, investors tend not to worry about the tracking error. When there is contango, on the other hand, an investor who rolls futures contracts, buys high and sells low. For example, the futures curve for WTI oil futures on September 21, 2015, is shown in Fig. 4. On this date, the nearest-term futures contract traded at a closing price of \$46.68 per barrel, while the next four futures contracts traded at \$46.96, \$47.43, \$48.60, and \$49.16, respectively. On the same day, the closing price for spot oil was \$46.67. On September 21, the front-month contract had one day to maturity. Thus, if oil prices did not move at all, and an investor were to buy the front-month contract, sell it on the next day, and buy the next month contract (i.e., holding the futures contract until maturity in this case), the investor would still lose one cent, which is about 0.022% over a day, or on an annualized basis about 5.43%.[21] Thus, independent of anything else occurring in the futures market, the futures investor might be expected to trail the spot oil index by about 5% per year.[22]

2.2. Returns from oil investing

Of ultimate importance to investors is the performance of different strategies for investing in oil. In this section, we will expand on the details of the performance of oil investing strategies. We will describe the returns from investing in actual oil futures, as well as ETPs that invest in oil futures.[23]

Table 3 contains the largest ETPs that invest in oil futures contracts ranked by AUM as of 2018. As mentioned earlier, the largest oil futures ETP is USO, with almost \$2 billion in AUM as of 2018. After that, there are OIL, UCO, DBO, and SCO which have another \$1.6 billion as a group. The smallest ETP in the top 20 is OILU, which is a levered crude oil fund with \$11 million under management.

Table 4 contains the annualized average daily statistics for the various futures contracts strategies as well as selected ETPs. Over the first period, 1994–2005, the average return to rolling the near-term contract was 26.96%. The average returns were similar for the second, sixth, and 12th month futures at 25.06%, 22.42%, and 18.61%, respectively. A significant portion of this return was from the "roll" of the contract or the backwardation in the marketplace, to a lesser extent for the near-term futures contract, which moved closely with spot oil. Spot oil over the same period had a return of 19.58%. Thus, this was generally a positive time for investing in oil futures, as oil futures substantially outperformed spot oil. Typically, oil futures investors do so on a leveraged basis, since oil futures require a small margin for investing. Thus, in addition to the oil futures return, a strategy of investing in oil futures will get an extra pick-up from investing the cash in a cash instrument. For our purposes, we assumed full collateralization of the strategy and used the one-month Treasury return as the cash return. The cash return over this period was 3.72% annualized. Thus, the total excess

[19] The performance does not change qualitatively, when one alters the days-to-expiration for rolling the contracts.

[20] The variable Days represents the percentage of trading days that the particular contract has been in contango.

[21] The daily number was annualized by multiplying by 250. The reader should be aware that a futures contract with one day to expiration is technically still anywhere from 10 to 14 days away from the first physical delivery date of oil. While the futures contract typically expires on the third business day prior to the 25th calendar day of the month preceding the delivery month, the first day of physical delivery of the oil is on the first of the delivery month and the last day is on the last day of the delivery month.

[22] We might expect arbitrageurs to balance the amount of contango in the oil market with the profits from exploiting extreme contango. However, this is not as simple as it sounds and will be discussed more when we consider the crowding of oil investing.

[23] In an untabulated analysis, we also examine the returns of the largest ETFs (XLE and VDE) and mutual funds (VGENX and FSENX) that invest in oil companies, which provide another way for investors to get exposure to the oil sector. We find that these investment vehicles track oil prices poorly and have a large tracking error (29% annualized).

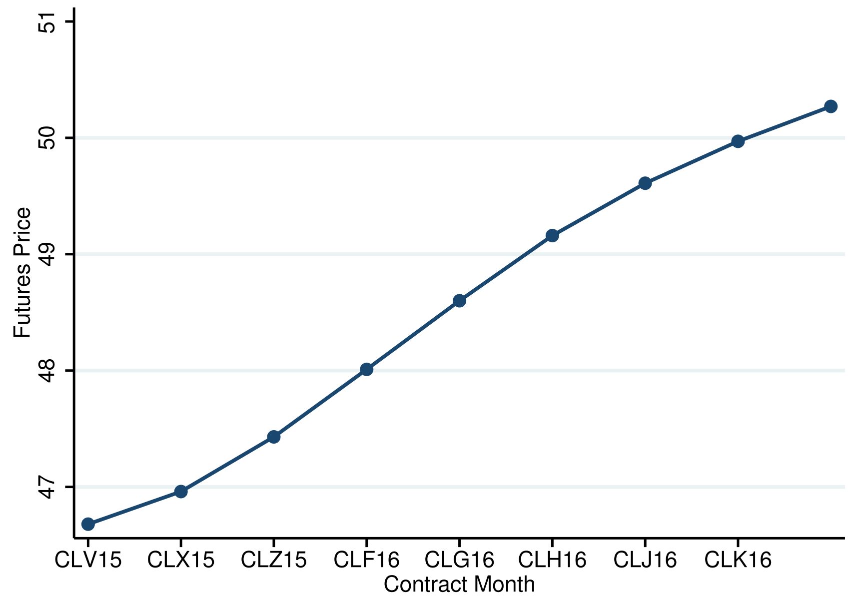

Fig. 4. The Term Structure of WTI Oil Futures Prices, September 21, 2015. This figure shows the term structure of WTI crude oil prices. "CL" is the Bloomberg ticker for WTI crude oil contracts, "15" or "16" represents maturity in 2015 or 2016, and "H" represents March, "J" represents April, "K" represents May, "M" represents June, "N" represents July, "Q" represents August, "U" represents September, and "V" represents October. These are standard conventions used by the futures trading exchanges.

Table 3
Largest 20 ETPs investing in Oil Futures.
Source: Bloomberg.

ETP Ticker	Fund Type	Security Name	Inception Date	AUM	E.R.	T.E.
USO	ETF	United States Oil Fund LP	04/10/2006	1973.09	0.72	N.A
OIL	ETN	iPath S&P GSCI Crude Oil TR	08/15/2006	628.88	0.75	7.41
UCO	ETF	ProShares Ultra Bloomberg CR	11/25/2008	437.40	0.95	26.89
DBO	ETF	PowerShares DB Oil Fund	01/05/2007	312.52	0.78	1.94
SCO	ETF	ProShares UltraShort Bloomberg Crude Oil	11/25/2008	207.10	0.95	82.57
DWT	ETN	VelocityShares 3x Inverse Crude Oil	12/09/2016	206.50	1.5	110.69
UWT	ETN	VelocityShares 3x Long Crude Oil	12/09/2016	117.63	1.5	54.93
UWTIF	ETN	VelocityShares 3x Long Crude ETN	02/07/2012	103.48	1.35	45.30
BNO	ETF	United States Brent Oil Fund	06/02/2010	92.40	0.9	N.A
USL	ETF	United States 12 Month Oil Fund	12/06/2007	81.86	0.79	N.A
OILB	ETN	iPath Series B S&P GSCI Crude Oil	11/18/2016	62.88	0.45	6.74
DTO	ETN	DB Crude Oil Double Short ETN	06/16/2008	59.18	0.75	78.73
UBRT	ETN	AxelaTrader 3x Long Brent Crude Oil	09/15/2017	41.89	1.35	N.A
OIIL	ETN	Credit Suisse X-Links WTI Crude Index	02/08/2016	38.10	0.55	7.15
OLEM	ETN	iPath Pure Beta Crude Oil ETN	04/20/2011	30.21	0.85	5.01
OILD	ETF	ProShares UltraPro 3x Short Crude Oil	03/27/2017	23.47	0.95	N.A
WTIU	ETN	ProShares Daily 3x Long Crude Oil	01/05/2017	22.14	1.45	55.17
WTID	ETN	ProShares Daily 3x Inverse Crude Oil	01/05/2017	15.55	1.85	110.85
DBRT	ETN	AxelaTrader 3x Inverse Brent Crude Oil	09/15/2017	13.64	1.65	N.A
OILU	ETF	ProShares UltraPro 3x Crude Oil	03/27/2017	11.86	0.95	N.A

Note: This table shows various statistics of the top 20 ETPs trading on U.S. exchanges ranked by AUM that invest in oil futures. Inception Date indicates the date the ETP was launched. AUM represents the assets under management of the fund as of February 19, 2018, expressed in millions of U.S. dollars. E.R. is the expense ratio of the fund as of February 19, 2018. Tracking Error is the standard deviation of the difference between the ETP and spot oil daily returns, estimated over the period February 19, 2017, to February 19, 2018.

performance of a futures-investing strategy was about 11.12%, 9.22%, 6.80%, and 3.09%, respectively, for the different maturity contracts.

We also measured the daily beta of the strategy with respect to spot oil. This is an indication of how much the futures strategy returns vary with spot oil returns. For example, a β=1, indicates that for a 10% change in the spot oil price, the futures strategy changes by 10%. Over this period, the strategy that tracked spot oil the best was accompanied by investing in the one-month or two-month futures contract with betas equal to 0.79 and 0.71, respectively. The 6-month and 12-month futures had betas of 0.53 and 0.42. Thus, for a 10% change in the spot price, the futures prices would move by 5.3% and 4.2%, respectively, on average. In other words, for a given movement in underlying spot prices, the 12-month futures price will move by less than the one-month futures price.

Despite the overall good performance of the futures investing strategy in this period, the tracking error is still quite high. That is, on an annualized basis, the futures investing strategy had a tracking error of 18.54% to 26.32% versus spot oil. Generally, oil futures investing does not track spot oil very well over a long period of time.[24]

From 2006 to 2017, the oil futures investing performance was entirely different. First and foremost, oil futures investing underperformed the spot oil benchmark. This is likely why this issue has received so much attention in the press. That is, oil futures investing

[24] Tracking error is measured as the daily standard deviation of the returns of the futures strategy minus the daily returns of spot oil annualized by multiplying by $\sqrt{250}$.

Table 4
Summary Statistics from Rolling Future Strategies and Oil ETPs.

Strategy	Futures					Cash	Spot			Tracking Error		
	Mean	"Roll"	"Spot"	S.D.	Sharpe	Mean	Mean	S.D.	Sharpe	Excess	T.E.	β
Investment Period: 1994–December 2005												
Fut1Roll0	26.96	3.15	23.76	34.55	0.66	3.72	19.58	38.47	0.40	11.12	18.54	0.79
Fut2Roll0	25.06	6.40	18.68	31.69	0.66	3.72	19.58	38.47	0.40	9.22	19.74	0.71
Fut6Roll0	22.42	8.23	14.25	24.97	0.74	3.72	19.58	38.47	0.40	6.80	23.10	0.53
Fut12Roll0	18.61	7.83	10.88	21.54	0.68	3.72	19.58	38.47	0.40	3.09	26.32	0.42
Investment Period: 2006–February 10, 2017												
Fut1Roll0	−5.73	−3.53	−2.20	37.63	−0.18	1.02	6.44	38.99	0.14	−11.12	11.46	0.92
Fut2Roll0	−6.11	−10.30	4.19	35.39	−0.20	1.02	6.44	38.99	0.14	−11.50	14.50	0.84
Fut6Roll0	−0.10	−7.45	7.36	31.69	−0.03	1.02	6.44	38.99	0.14	−5.49	17.44	0.73
Fut12Roll0	1.56	−4.48	6.04	28.24	0.02	1.02	6.44	38.99	0.14	−3.86	19.88	0.63
Investment Period: 2009–February 10, 2017												
Fut1Roll0	−2.26	−3.72	1.46	36.29	−0.06	0.07	9.18	37.18	0.25	−11.32	9.64	0.94
Fut2Roll0	−4.30	−10.54	6.24	34.15	−0.13	0.07	9.18	37.18	0.25	−13.36	12.78	0.86
Fut6Roll0	0.83	−7.83	8.66	30.40	0.03	0.07	9.18	37.18	0.25	−8.24	16.41	0.74
Fut12Roll0	1.50	−4.73	6.23	26.75	0.05	0.07	9.18	37.18	0.25	−7.61	19.16	0.63
	ETPs using Oil Futures Contracts											
USO	−7.27	.	.	33.67	−0.22	0.07	9.18	37.18	0.25	−16.41	15.37	0.82
OIL	−9.79	.	.	35.76	−0.28	0.07	9.18	37.18	0.25	−18.93	18.81	0.83
UCO	−17.72	.	.	65.29	−0.27	0.07	9.18	37.18	0.25	−26.86	35.44	1.59
DBO	−4.35	.	.	29.73	−0.15	0.07	9.18	37.18	0.25	−13.49	19.00	0.69
SCO	10.62	.	.	65.77	0.16	0.07	9.18	37.18	0.25	1.48	100.77	−1.60

Note: The table presents various statistics with respect to futures and spot returns of oil. For each futures contract, the first number indicates the specific futures contract, either 1, 2, 6, or 12, depending on whether the nearest-term, second, sixth, or 12th contract is used. The second number represents the roll date. Thus, a "0" indicates the contract was theoretically rolled on the expiration date of the front contract. Mean represents the annualized average return calculated as the average daily return multiplied by 250, "Roll" represents the annualized return of the expected roll. "Spot" represents the annualized return of the "spot" change according to the formula presented in the Appendix, $r^i_{t,t+k,d} = \underbrace{\frac{F^*_{t,d,m-k} - F^i_{t,d,m}}{F^i_{t,d,m}}}_{\text{"Expected Roll"}} + \underbrace{\frac{F^i_{t+k,d,m-k} - F^*_{t,d,m-k}}{F^i_{t,d,m}}}_{\text{"Spot Return"}}$. Cash represents the annualized average return of a one-month Treasury bill. S.D. represents the annualized standard deviation of the returns computed as the daily standard deviation multiplied by $\sqrt{250}$. Sharpe represents the annualized Sharpe ratio computed as the average return of the respective instrument minus the risk-free rate of return divided by the volatility of that difference. Excess represents the annualized average return difference between the futures investing strategy plus cash and the actual spot oil returns, except in the case of ETPs, where it represents their net-of-fee excess returns over spot oil. T.E. represents the annualized tracking error of the futures strategy plus its cash return on collateral, which is assumed to get 100% of the cash return, and the spot return of oil. β is the beta from a regression of the daily return of the futures contract against the daily spot return in oil. All values are multiplied by 100, except for β, so as to represent percentage points.

did not track extremely well in the earlier period as well; however, it outperformed spot oil, so investors were less concerned with the tracking issue. In fact, if one observes only the tracking error, it was actually lower in the 2006 to 2017 period and the daily beta estimates showed that on average, the oil futures strategy moved more in line with spot oil. Nevertheless, the average returns from the futures strategy underperformed spot oil by −11.12%, −11.50%, −5.49%, and −3.86%, respectively. Over this period, the average annualized spot oil return was 6.44%, while all of the futures' returns were negative, with the exception of the 12-month contract. Much of the negative returns can be attributed to the "roll" effect.[25] The "roll" effect is the average estimated loss from rolling futures contracts due to the fact that futures prices are higher than spot prices on average (i.e., the contango effect).[26] In this period, this issue was most severe for the second futures contract, which suffered an annualized loss of about 10% due to contango in the oil futures market (see the "Roll" component).

The ETPs that invest in oil futures have similar characteristics to the underlying oil futures contracts. To make the analysis meaningful, we chose the period from 2009 to 2017, because more oil ETPs existed. In Table 4, one can see that over this period, the ETPs investing in oil futures contracts suffered a similar fate to the oil futures investing strategies. For example, over the period, USO had a −7.27% return, while spot oil had a 9.18% return. This represented an underperformance to spot oil of −16.41%. For OIL and UCO, the underperformance was even larger at −18.93% and −26.86%, respectively. DBO did slightly better with an underperformance of −13.49%.[27] In all cases, the tracking error of these ETPs was all above 15% annually.

Overall, the story is that investing in oil creates a substantial tracking error with respect to spot oil. Some of this is due to the fact that spot oil is not an appropriate benchmark, because it fails to account for storage and other related costs. Part of the problem is that contango has increased in futures markets, making the difference in performance between oil futures investing and spot oil more negative.

The cumulative effects from oil investing are even more startling. These results are shown in Table 5. This paints a clearer picture of what is going on with futures investing. For example, for the nearest-term futures contract strategy (Fut1Roll0) over the period 1994 to 2005, the cumulative return of the strategy was 1714.34% versus the actual

[25] The methodology for computing the roll effect is explained in the Appendix C to this paper.

[26] Note that there are no immediate cash outflows (a loss) at the roll date. Still, contango, in particular the steepness of the term structure of futures, affects the performance of a long-term investment in futures. Under the assumption that the spot price stays constant, the return of the futures is determined only by the roll component, which depends on the difference between futures and spot prices (the basis).

[27] Presumably, the main reason for DBO's better performance was because this ETF chooses to use futures contracts with the least amount of contango, and thus is expected to lose the least from futures roll. In fact, over the same period, only the 6-month and 12-month futures strategy had positive annualized returns.

Table 5
Cumulative Returns from Futures Rolling.

Strategy	Futures Investing						
	"Roll"	"Spot"	Futures	Cash	Fut & Cash	Spot	Excess Return
Investment Period: 1994–December 2005							
Fut1Roll0	51.66	1085.81	1140.60	56.34	1714.34	330.30	1384.03
Fut2Roll0	189.18	817.57	1005.81	56.34	1518.58	330.30	1188.28
Fut6Roll0	236.49	679.13	913.57	56.34	1420.87	330.30	1090.56
Fut12Roll0	185.00	423.61	606.21	56.34	972.19	330.30	641.89
Investment Period: 2006–February 10, 2017							
Fut1Roll0	−19.83	−56.28	−76.11	12.04	−73.04	−11.82	−61.22
Fut2Roll0	−60.90	−14.07	−74.97	12.04	−71.76	−11.82	−59.94
Fut6Roll0	−60.44	16.84	−43.60	12.04	−36.45	−11.82	−24.62
Fut12Roll0	−39.64	15.86	−23.78	12.04	−14.40	−11.82	−2.57
Investment Period: 2009–February 10, 2017							
Fut1Roll0	−27.02	−24.41	−51.42	0.60	−50.79	20.72	−71.51
Fut2Roll0	−64.95	8.65	−56.30	0.60	−55.73	20.72	−76.45
Fut6Roll0	−55.84	29.17	−26.67	0.60	−25.80	20.72	−46.52
Fut12Roll0	−32.24	16.61	−15.63	0.60	−14.91	20.72	−35.63
	Largest ETPs using Oil Futures						
USO	.	.	.	0.60	−65.25	20.72	−85.96
OIL	.	.	.	0.60	−73.41	20.72	−94.13
UCO	.	.	.	0.60	−95.91	20.72	−116.63
DBO	.	.	.	0.60	−51.16	20.72	−71.88
SCO	.	.	.	0.60	−59.59	20.72	−80.30

Note: The table presents various statistics with respect to the cumulative futures and spot returns of oil. For each futures contract, the first number indicates the specific futures contract, either 1, 2, 6, or 12, depending on whether the nearest-term, second, sixth, or 12th contract is used. The second number represents the roll date. Thus, a "0" indicates the contract was theoretically rolled on the expiration date of the front contract. "Roll" represents the cumulative return over the period from the expected roll, "Spot" represents the cumulative return over the period from the "spot" based on the formulas presented in the Appendix, $r^{1,N}_{roll} = \sum_{i=1}^{N} r^{i}_{roll} \prod_{j=1}^{i-1}(1+r_j)$ and $r^{1,N}_{spot} = \sum_{i=1}^{N} r^{i}_{spot} \prod_{j=1}^{i-1}(1+r_j)$. Futures represents the cumulative return of the rolling futures strategy, Cash is the cumulative return from investing every day in a one-month Treasury bill. Spot is the cumulative return of spot oil, and Fut & Cash represents the returns from investing in futures and receiving 100% of one-month Treasury on the collateral, except in the case of ETPs, where it represents their net-of-fee cumulative returns. Excess Return represents the return of the strategy or investment product minus the cumulative return of spot oil. As stated in the text, we removed days with missing data, mainly missing spot data. However, for a couple of day, we had missing data for the 6-month and 12-month contract on November 5, 1999, for the former and September 14, 2001, for the latter. All values are multiplied by 100, so as to represent percentage points.

spot of 330.30%. This represented 1140.60% cumulative return from investing in futures, an additional 56.34% from investing the collateral in cash, and the remaining amount (with some rounding error) was due to the benefit of compounding a portfolio consisting of the diversification benefits of cash and futures as opposed to either in isolation. The cumulative "spot" component of the return decomposition consisted of 1085.81% and the "roll" component of the decomposition delivered a gain of 51.66% due to rolling down an on-average-backwardated oil futures curve with a net effect of 1140.60%. The excess performance of a futures rolling strategy varied by contract, but for the nearest-term contract rolled at expiration (Fut1Roll0), the cumulative excess return was 1384.03% (1714.34 minus 330.30).

Contrary to the earlier period, it was not possible to outperform the underlying spot market by investing in oil futures during the 2006 to 2017 period. During this time, the same contract and roll (Fut1Roll0) produced a cumulative return (futures and cash) of −73.04% compared to spot oil of −11.82%. The futures return alone, without considering cash, was −76.11%. This would be quite disheartening for oil investors if their benchmark was spot oil. The same story applies to ETPs that invested in oil futures. There was a large underperformance in spot oil, which was as high as −116.63% to as low as −71.88%.

3. Challenge 2: Investment crowding and the financialization of commodities

In recent years, a phenomenon known as crowding has been noted as an important consideration when investing in securities (Chincarini (1998, 2012), Cahan and Luo (2013), Anton and Polk (2014), Ibbotson and Idzorek (2014), Menkveld (2014), Chue (2015), Blitz (2017), Zhong et al. (2017), Bruno et al. (2018), Chincarini (2017), Kinlaw et al. (2018), Baltas (2019), Brown et al. (2019), and Marks and Shang (2019)). Crowding occurs when there is an abnormal concentration of investors on one particular side of a market. Crowding matters because it can distort the risks and returns of an investment strategy. The same sort of distortions may have occurred in the oil futures market. These distortions may have been exacerbated in the last decade by the financialization of the commodity markets.

Perhaps one of the most extreme cases of crowding involved crude oil futures on April 20, 2020. The price of the near-term contract (May 2020) dropped to -$37.63 per share. As global demand for oil has plummeted due to the coronavirus crisis and storage capacity for crude oil was diminishing, many participants wanted to sell oil, thus pushing the price down. Speculators, who ultimately take the other side of the position, ensuring orderly behavior of the markets, also had no incentive to buy cheap oil due to the potential difficulty in storing oil. Thus, one side of the market sold and the other side of the crude oil market disappeared, causing oil to decrease to almost -$40 per barrel.[28]

3.1. Impact on futures prices

In order to think about the potential impact of crowding and the financialization of commodities on the oil futures market, it might help to review some basic concepts of how oil futures are priced in equilibrium. In particular, one can model the relationship between the spot price of oil and the futures price as follows:

$$F_{t,m} = S_t e^{(r+u-y)m} \tag{2}$$

[28] For more information on this event, see https://onh.ccd.myftpupload.com/pres/Oil_Price_Presentation_SMF_04_23_2020.pdf.

where S_t is the spot price of the commodity and $F_{t,m}$ is the futures price of the commodity expiring at date $t+m$, r is the relevant interest rate, u is the storage costs of oil, and y is the convenience yield of the commodity, which represents the price discrepancy that we do not understand, typically referred as the benefit to owning the spot product, all of which can vary over time. Whenever the sum of the interest rate and storage costs are greater than the "convenience yield," then the oil market is in contango. For example, when the convenience yield is equal to zero, the oil futures market would be in contango.[29]

Crowding of the commodity refers to whether there is a concentration of investors on one particular side of the oil futures market. It is related to financialization to the extent that an increase in index investing contributes to crowding, but crowding can also occur without index investors. For example, in the past, the natural hedgers of oil futures were presumably oil producers, who would have tended to be sellers of the commodity. This would lead to a relative benefit to buyers of the commodity. These buyers would be considered liquidity providers and consequently obtain a premium for this service, as described by Keynes (Keynes (1930)). That is, Keynes believed we would expect normal backwardation in the oil futures market (i.e., $E(S_T) > F_{t,T}$).

In recent years, the crowd may have tilted toward the other side as airlines and other users have hedged oil by buying the commodity in order to smooth fluctuations in their businesses. In addition, with the availability of oil-investing vehicles, there is a larger concentration of investors on the side of purchasing oil. Thus, as investors flooded the buy side of the oil market, this buying pressure may have affected futures prices and contributed to shifting the market into normal contango (i.e., $E(S_T) < F_{t,T}$).

Due to the increase of capital allocated to the futures market, we posit that investors have crowded the oil market and have impacted the slope of the term structure. A natural question one might ask is why arbitrageurs have not fixed this problem. First, not everyone can do this easily and efficiently. For instance, arbitraging a buy-side distortion requires selling oil futures and buying and storing spot oil, which is not easy. Also, the number of those wishing to arbitrage may be small in relation to the crowds on the investment side. Furthermore, as pointed out by Singleton (2014), there are investment frictions that limit arbitrage activity in the futures market. Some theoretical models have been proposed to explain how financialization may affect commodity futures prices. Acharya et al. (2013) examine the role of financial constraints of financial intermediaries, whereas Hamilton and Wu (2014) focus on the role of liquidity. Sockin and Xiong (2015) analyze the effects of informational frictions in commodity markets. Basak and Pavlova (2016) analyze an endowment economy with two types of agents, a standard futures market participant and index investors. Index investors have preferences benchmarked to the index, and this causes the futures returns of those commodities in the index to have higher correlations with each other and with the stock return than those outside the index. Overall, there is sufficient theoretical support for an impact of uninformed order flows due to the increase of passive investing on futures prices. Therefore, it is plausible that this growth in investors has caused contango to increase and oil futures returns to suffer.

3.2. Empirical tests

Testing for crowding and the impact of financialization is difficult in the oil market. The main issue is the lack of detailed high-frequency data about the different trading positions, particularly for index investors.[30] The data that we have available are the weekly aggregate positions from the Commitments of Traders (COT) reports (see Appendix A for more details about the data). We supplement these data with data on ETPs, which are available at a daily frequency. We examine the impact of crowding not only on futures returns, which has been the focus of the existing literature, but also on the different components of futures returns, and in particular on contango and the difference between spot and futures returns. It is also difficult to distinguish between crowding and financialization. When we use daily data, we can test the impact of passive investing capital on the futures market, which is a test of the effect of financialization. However, at the weekly level, we combine several variables to capture aggregate demand pressures and we interpret the analysis as a test of crowding.

We know that the difference in futures returns, r_f, and spot returns, r_s, is related to the cost of carry $\Psi_t = r_t + u_t - y_t$ and therefore to the interest rates, storage costs, and convenience yields (see Appendix E) according to the following equation:

$$r_{f,t} - r_{s,t} = (m-1)\Delta\Psi - \Psi_{t-1} = m\Delta\Psi - \Psi_t \tag{3}$$

where $\Delta\Psi = \Psi_t - \Psi_{t-1}$. We posit that the crowding of the futures market affects the commodity-price relationship through the variable, y, the convenience yield. Thus, in order to understand whether crowding might contribute to both contango and the tracking error between oil futures and spot oil, we estimate the following equation using weekly and daily data:

$$Y_t = \alpha + \gamma CROWD_{t-1} + \boldsymbol{\Lambda}\mathbf{X}_{t-1} + Y_{t-1} + \epsilon_t \tag{4}$$

where Y_t is either the futures return, contango, or the difference between futures and spot returns.[31] $CROWD_{t-1}$ is a variety of proxies for crowding and $\mathbf{X}_{t-1}$ are control variables thought to affect the dependent variable.

Table 6 contains the proxies that we use to measure crowding. Some of these measures represent crowding from different participants. One problem with these measures is that they are not precise and represent aggregate statistics from the COT report. The other issue is that most of them are available only at the weekly frequency at best, which might be too long to capture the immediate effects of crowding. Perhaps the most reliable data are the data on fund flows and assets under management (AUM) of ETPs that invest in oil futures. These data are daily and are also a fair depiction of the amount of dollars chasing the long side of the oil futures market.[32] Given the large number of proxies, we aggregate their information content using principal component analysis and extract the first two principal components (PCs), which we include in the regression. When we use weekly data, we extract the PCs from all the variables listed in Table 6. With daily data, we have fewer variables because we lose the data from the COT report, which are available only at the weekly frequency. Therefore, it is less advantageous to use the

[29] There are various theories on what the term structure of oil actually signifies. Thus, we prefer to be general about the convenience yield. Some have argued that when inventories are low, there is a benefit to holding the physical commodity, hence convenience yields are high and spot prices trade higher than futures prices. The expectations hypothesis argues that a counteracting force can be the expectations of market participants. That is, they may believe futures spot prices might be lower, causing a downward-sloping futures curve. See Gorton et al. (2012) for a discussion of hedging premiums. Some people express this relationship as $r - \delta$, where δ represents the net convenience yield or convenience yield net of storage costs. Gorton and Rohwenhorst (2006) discuss the "no-arbitrage" relationship between oil futures and spot oil.

[30] Some authors (e.g., Singleton (2014)) have used CFTC data from the agricultural commodity market, which provide index-investors positions, and the compositions of the S&P GSCI and the Dow Jones UBS Commodity Index to approximates positions in the oil futures market. However, Irwin and Sanders (2012) raise criticisms of this approach. For this reason we decided against using this approach.

[31] We cannot directly model the convenience yield because data on storage costs are not available for the full sample period.

[32] For AUM and fund flows, we used only the data for the four largest oil-investing ETPs (USO, OIL, UCO, and DBO) in order to have enough data points for the analysis. These four ETPs have the vast majority of the AUM of all the ETPs. The most recent contract is UCO, for which we have data starting from November 25, 2008.

Table 6
Proxy Measures of Crowding in the Oil Market.
Source: COT and Bloomberg.

Number	Measure	Computation	Purpose
1.	Volume as Fraction of Open Interest	$\frac{Volume}{OI}$	Measures whether an abnormal amount of volume is putting pressure on the futures market. Source: Exchanges and Bloomberg.
2.	Net Concentration of 4 Largest Players	$C_L^4 - C_S^4$	Measures the percentage of futures market long by top 4 participants minus the percentage of market short by same participants. Source: COT
3.	Net Concentration of 8 Largest Players	$C_L^8 - C_S^8$	Measures the percentage of futures market long by top 8 participants minus the percentage of market short by same participants. Source: COT
4.	Producer Pressure	$\frac{PL-PS}{OI}$	Measures the difference between producer longs minus producer shorts as a percentage of total open interest. Producer longs are defined to be producers, processors, merchants or dealers. Source: COT
5.	Money Manager Pressure	$\frac{MMCL-MMCS}{OI}$	Measures the difference between money manager longs minus money manager shorts as a percentage of total open interest. We exclude swap dealers and other reportables contained in the COT database. Source: COT
6.	Commercial Pressure	$\frac{CL-CS}{OI}$	Measures the difference between commercial longs minus commercial shorts as a percentage of total open interest. Commercial longs are defined to entities involved in businesses that require futures or options for hedging as per form CFTC Form 40. Source: COT
7.	Non-Commercial Pressure	$\frac{NCL-NCS}{OI}$	Measures the difference between non-commercial longs minus non-commercial shorts as a percentage of total open interest. Non-Commercial longs are defined as those that are not commercial. We exclude swap dealers and other reportables contained in the COT database. Source: COT
8.	ETP Fund Flows as Fraction of Open Interest	$\frac{\text{ETP flows}}{OI}$	Measures the total net flows in the four largest ETPs (USO, OIL, USO, and DBO) that invest in oil futures divided by total open interest converted in dollar values. Source: Bloomberg
9.	Change in AUM	ΔAUM	Measures the total change in assets under management (in millions of U.S. dollars) of the four largest ETPs (USO, OIL, USO, and DBO) that invest in oil futures. Source: Bloomberg
10.	Change in AUM as Fraction of Open Interest	$\frac{\Delta AUM}{OI}$	Measures the total change in assets under management of the four largest ETPs (USO, OIL, USO, and DBO) that invest in oil futures divided by total open interest converted in dollar values. Source: Bloomberg

Note: The table presents some of the proxy variables used to measure crowding in the oil market. For the variable volume as fraction of open interest we use average daily trading volume for the last 20 trading days in the daily analyses.

PCs, and we use instead data on fund flows, on AUM of ETPs that invest in oil futures, and volume data from the futures markets.[33]

We also consider control variables that might explain oil futures and spot price changes, but unfortunately, many of them were of a monthly frequency, which could cause important relationships to be masked. Thus, we included only those that were at least at a weekly frequency, such as inventory or stock levels of oil.[34] We also include the variables suggested by Singleton (2014), which are the change in overnight repo transactions on Treasury bonds and bills by primary dealers, and the returns on the MSCI Emerging Market Asia and the S&P 500 indices. The repo positions should capture changes in the balance sheet of large financial institutions, which could affect their willingness to commit capital to risky investments. These data are from the New York Federal Reserve Bank and are available only at the weekly frequency. The stock index returns should control for the possibility that investors' positions are affected by developments in the global equity markets.

Before presenting the results, we summarize some of the data of our crowding proxies in Table 7. In our data, the average daily volume divided by the average daily open interest was 53.12%, with a maximum of 98.92% and a minimum of 16.84%.[35] The net concentration of the four largest players long the futures market was as high as 11% and as low as −3.3%, with an average of 2.90% long. The concentration of the eight largest players long the futures market was as high as 13.1% and as low as −2.5%, with an average of 3.35%. Producer Pressure was generally negative, with an average of −9.30%, a high of 2.76%, and a low of −22.24%. Money Manager Pressure averaged about 10.66%, with a high of 20.51% and a low of −1.12% during our sample period. Commercial Pressure and Non-Commercial Pressure were on opposite sides of the futures curve on average, with commercial players being −13.79% short, while non-commercial players were 13.06% long. These numbers are related to the discussion on the different holders of commodity futures and how that may have changed over time, as discussed in Section 3.1. ETP flows are expressed as a percentage of open interest and are a smaller number at 0.07% on average, but with a high of 6.25% and a low of −4.65%.[36] The change in AUM daily average is about $7.26 million, with a high of $1 billion and a low of $-675 million. The change in AUM as a percentage of open interest is very small at 0.02% on average, with a high of 1.57%. The crowding proxies generally seem to have enough variation that they might have an effect on futures returns, which is the next topic of discussion.

The empirical results from testing the crowding measures on different measures of futures returns and contango are presented in Table 8 using weekly data and in Table 9 using daily data.[37]

We first consider the effect on the futures returns using weekly data. We focus on the first futures (the front) contract because it is the most important and most liquid contract. Consistent with the existing literature, the impact on futures returns is weak, and the first PC is only marginally significant. Next, we analyze the effect on the difference between the first futures returns and spot returns and contango. Here,

[33] More precisely, we use the change in AUM as a percentage of open interest, total flows as a percentage of open interest, and volume as a fraction of open interest.

[34] The COT data are reported weekly on Tuesday, while inventory or stock data are reported by the EIA weekly on Friday. Thus, to combine the data, we aligned the Friday inventory data of the week before with the Tuesday COT data. Hence, in effect, the inventory data are slightly stale. We also tried to include proxies for storage costs from the LOOP futures contracts, but they only started to trade in March 2015.

[35] For open interest and volume, we used only the first 15 contracts in the oil futures market, which represent the majority of volume and open interest and are the most relevant for oil investing vehicles.

[36] To capture the cumulative impact and to reduce the number of zeros, we sum the daily flows in the week. We also computed the average of the daily flows instead of the sum and the regression results are very similar.

[37] We compute futures returns assuming that the roll date is the expiration date of the front contract. We tried to use alternative roll dates and obtained similar results.

Table 7
Summary Statistics of Crowding Proxies.
Source: COT and Bloomberg.

Panel A: Summary Statistics of Crowding Proxies

Measure	Obs	Mean	Median	Std. Dev.	Min	Max
1. Volume/OI	431	53.12	52.12	14.00	16.84	98.92
2. Net Concentration top 4	431	2.90	3.00	3.38	−3.30	11.00
3. Net Concentration top 8	431	3.35	3.10	3.46	−2.50	13.10
4. Producer Pressure	430	−9.30	−10.63	6.43	−22.24	2.76
5. Money Manager Pressure	430	10.66	11.17	4.18	−1.12	20.51
6. Commercial Pressure	431	−13.79	−14.21	6.68	−28.62	20.90
7. Non-Commercial Pressure	431	13.06	13.58	6.46	−10.80	26.67
8. ETP flows/OI	429	0.07	−0.01	1.02	−4.65	6.25
9. Change in AUM (in million $)	424	7.26	−22.36	233.28	−675.06	1016.58
10. Change in AUM/OI	424	0.02	−0.02	0.34	−1.40	1.57

Panel B: Correlation Matrix of Crowding Proxies

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Volume/OI	1.00									
2. Net Concentration top 4	0.49	1.00								
3. Net Concentration top 8	0.46	0.95	1.00							
4. Producer Pressure	−0.51	−0.74	−0.70	1.00						
5. Money Manager Pressure	−0.28	−0.68	−0.69	0.37	1.00					
6. Commercial Pressure	0.30	0.62	0.62	−0.50	−0.81	1.00				
7. Non-Commercial Pressure	−0.31	−0.59	−0.58	0.52	0.77	−0.99	1.00			
8. ETP flows/OI	0.10	0.08	0.08	0.02	−0.23	0.09	−0.08	1.00		
9. Change in AUM (in million $)	0.16	0.06	0.07	0.00	−0.10	0.08	−0.06	0.50	1.00	
10. Change in AUM/OI	0.14	0.06	0.08	−0.01	−0.12	0.10	−0.08	0.57	0.96	1.00

Note: The table presents summary statistics and correlations for the proxy variables used to measure crowding in the oil market. The summary statistics are computed over the period November 25, 2008, to February 7, 2017, using weekly data. Complete definitions of the proxy variables can be found in Table 6. The COT data are reported weekly; for example, in 2018, reports were published on 03/27/2018, 04/03/2018, and 4/10/2018, and so on. Due to this, we adjusted our daily series to correspond to the same report dates of the COT. For example, Volume is the average daily volume from one report date to the next report date, and OI (open interest) is the average daily open interest from one report date to the next report date. We also take the sum of volume and open interest across the first 15 contracts. We take the weekly change in AUM and the sum of the daily flows from one report date to the next report date for ETP flows. All data are reported in percentage terms, except for change in AUM, which is reported in millions of U.S. dollars. Panel B presents the correlation matrix of the proxy variables used to measure crowding in the oil market. The correlations are computed over the period November 25, 2008, to February 7, 2017.

the results are significant. The effect of crowding captured by the first PC has a negative impact on futures returns minus spot returns, whereas the effect on contango is positive. We also consider the impact on the futures–spot difference computed using the average return of the first 15 futures contracts, and the average contango in the first 15 contracts.[38] The negative (positive) impact of crowding on the different components of returns (contango) is confirmed. In an untabulated analysis, we include the crowding proxies individually. The most significant effects stem from the concentration of the top four and top eight futures players, which are the best variables to capture a crowding effect. As this concentration increases, futures returns minus spot returns decline and contango increases. Overall, the weekly data reveal that there is a link between crowding in the oil futures market and components of futures returns and contango.

Table 9 shows the regressions using daily data. Using daily data, there is more power given the larger number of observations, but we lose the data from the COT report. We focus on two measures of the impact of financialization. One measure obtained from the ETP data is either the change in AUM or ETP flows as a fraction of the open interest. The other measure is the past futures volume divided by the open interest. Consistent with the existing literature, there is little evidence of a significant impact of ETP assets and flows on futures returns. However, when we predict futures returns minus spot returns, we find that the change in AUM and ETP flows have a negative and significant coefficient. There is also some evidence that past volume has a positive impact on contango.

3.2.1. VAR analysis

To provide further evidence of the impact of crowding and financialization on the oil futures market, we estimate the following VAR model:

$$Y_t = \alpha + \beta Y_{t-1} + \epsilon_t \tag{5}$$

where Y_t is a vector that includes one of the various measures of futures returns or contango and the first two PCs when using weekly data, and the ETP measures and daily volume when using daily data. The number of lags in the VAR is specified based on the Schwarz Bayesian information criterion and varies from one to four lags, depending on the specification. Table 10 presents the results using weekly and daily data. We present only the p-values of Granger-causality tests on whether the crowding measure affects returns and contango. As documented in the literature, using weekly data, crowding has an insignificant impact on futures returns. The first two PCs have an insignificant effect on futures returns, as we cannot reject the null hypothesis. However, the first PC has a significant impact on the other components of returns and contango. In particular, the first PC Granger causes changes in futures returns minus spot returns and contango. The second PC is also significant in predicting the return difference. When we use daily data, there are significant effects even for the futures returns. This confirms that it is important to use daily data to increase the power of the test. In particular, there is evidence that the ETP variables and volume Granger cause change in returns and contango. The results are confirmed when we run the tests using a VAR that includes the control variables.

3.3. ETFs purchases of futures

The daily tests show that there is some evidence of an impact of passive investing through ETPs on futures prices consistent with the financialization of commodities. Although ETP investors tend to be unsophisticated, one concern is that ETP flows may be driven by expectations regarding futures oil prices. To address this potential

[38] We focus on the first 15 contracts because on average they represent 95.12% of the total volume across all the 51 contracts. Also, the top four ETPs that we consider purchase only up to the first 13 contracts.

Table 8
Regressions of Various Measures of Futures Returns and Contango on Crowding Principal Components.

Indep. Variables	Ret fut	Ret diff	Contango	Ret diff avg	Contango avg
	(1)	(2)	(3)	(4)	(5)
	Time Frequency: Weekly				
First PC	0.426*	−0.323***	0.032***	−0.392***	0.012***
	(0.241)	(0.100)	(0.011)	(0.150)	(0.005)
Second PC	−0.089	−0.435	0.005	−0.325	0.000
	(0.338)	(0.268)	(0.014)	(0.289)	(0.003)
Δ Inventory	−0.610***	0.030	0.005	0.233**	0.006***
	(0.210)	(0.100)	(0.006)	(0.102)	(0.002)
Δ Repo Transactions	−0.015	0.171***	0.003	0.091	0.001
	(0.228)	(0.056)	(0.007)	(0.101)	(0.001)
MSCI Asia Ret	−0.459	−0.030	−0.018	0.148	0.002
	(0.366)	(0.130)	(0.011)	(0.197)	(0.003)
SP&500 Ret	−0.030	0.293	0.013	0.352	0.001
	(0.403)	(0.254)	(0.010)	(0.257)	(0.004)
Lag Ret Futures	−0.051				
	(0.352)				
Lag Ret diff		−0.240			
		(0.162)			
Lag Contango			0.004		
			(0.017)		
Lag Ret diff avg				−0.386	
				(0.429)	
Lag Contango avg					0.064***
					(0.008)
Constant	−0.039	−0.357***	0.030***	−0.270**	0.012***
	(0.247)	(0.114)	(0.010)	(0.133)	(0.004)
R-sqr	0.034	0.146	0.044	0.101	0.776
Obs	423	423	423	423	423

Note: This table reports results from regressions of various weekly measures of returns and contango on the first and second principal components (PCs) obtained from crowding variables and controls for the period from November 25, 2008, to February 7, 2017. The dependent variables include the first futures returns, the difference between the first futures returns and spot returns, contango, the futures–spot difference computed using the average return of the first 15 futures contracts, and contango in the average first 15 contracts. The crowding variables that are used to extract the PCs are defined explicitly in Table 6. The control variables include the change in U.S. Oil Inventory, the weekly change in overnight repo transactions on Treasury bonds and bills by primary dealers, and weekly returns on the MSCI Emerging Market Asia and the SP&500 indices. All the independent variables are standardized. The standard errors of coefficients are listed directly under the parameter estimates in parentheses.

*indicates statistical significance at the 10% using robust standard errors.

**indicates statistical significance at the 5% using robust standard errors.

***indicates statistical significance at the 1% using robust standard errors.

endogeneity problem, it is important to identify changes in demand which are not based on information about futures price movements. Our identification strategy is based on the initiation of purchases of futures by ETFs. These purchases are driven by the expiration cycle of the futures rather than by price expectations of ETF investors. We want to test whether the volatility of the futures returns and the correlation between the returns of different futures contracts are higher during the dates when ETFs first purchase futures contracts.

The idea behind using correlation as a measure of crowding is based on the idea of excess comovement. Traditional economic theory states that the sensitivity of asset returns to common factors reflects similar changes in fundamental values. However, Barberis et al. (2005) find that both frictions and investor sentiment are also relevant drivers behind correlated returns among assets. Furthermore, Anton and Polk (2014) find that the degree of shared ownership by active mutual funds contributes to excess return comovement measured by the stock return correlation. There is also theoretical support for an increase in correlation due to style and index investing. For example, Barberis and Shleifer (2003) argue that style investing generates comovement between individual assets and their styles, and Basak and Pavlova (2016) propose a model where index investors have preferences benchmarked to the index, which cause the futures returns of those commodities in the index to have higher correlations with each other. Therefore, inspired by these studies, several papers use the return correlation as a measure of crowding. For example, Cahan and Luo (2013), Baltas (2019), and Lou and Polk (2020) use correlation to identify crowding in equity momentum strategies and quantitative equity strategies.

We use a sample of daily holdings of futures by ETFs obtained from ETF Global database. The data are available for only six ETFs (OILD, OILU, SCO, UCO, USL, USO) with a limited time series (starting mainly in December 2015). With daily holdings, we can observe the first day when a new futures contract enters into the portfolio. We identify and create a dummy variable for these dates. Next, using intraday data purchased from the TickData database, we compute 5-minute returns, which we use to obtain daily standard deviation and correlations. We want to test whether volatility and correlations are higher for the days when there are non-fundamental changes in demand driven by ETFs trading. Hence, we run a regression of daily volatility or correlation on the dummy variable that captures the first time ETFs purchase a futures contract. Table 11 provides the results and shows that, even when we control for year and day of the week effects, we observe higher volatility and correlations between the returns of the front contract and the back contracts when there is ETP activity.

3.4. Additional tests for the financialization of the oil market

To provide further support for the financialization of the oil market, we run three additional tests that corroborate the evidence of a change in the behavior of oil futures prices in the last decade. First, we examine the links between the oil market and the equity market. There is some evidence that financialization increases links among different commodities and other asset classes. For example, Tang and Xiong (2012) document that the correlations among commodities included in the main index funds are stronger than for commodities not included. Adams and Glück (2015) study the transmission of stock market shocks

Table 9
Regressions of Various Measures of Futures Returns and Contango on Crowding Measures.

Indep. Variables	Ret fut	Ret diff	Contango	Ret diff avg	Contango avg	Ret fut	Ret diff	Contango	Ret diff avg	Contango avg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Time Frequency: Daily									
$\frac{\Delta\ \text{AUM}}{\text{OI}}$	0.172	−0.101***	0.003	−0.147**	−0.002					
	(0.143)	(0.030)	(0.007)	(0.064)	(0.001)					
$\frac{\text{ETP flows}}{\text{OI}}$						0.082	−0.112*	0.010	−0.164*	−0.000
						(0.106)	(0.061)	(0.008)	(0.085)	(0.001)
$\frac{\text{Volume}}{\text{OI}}$	0.108**	−0.044**	0.019***	−0.056**	0.002	0.105**	−0.047**	0.019***	−0.057**	0.002*
	(0.048)	(0.019)	(0.006)	(0.027)	(0.001)	(0.048)	(0.019)	(0.006)	(0.027)	(0.001)
MSCI Asia Ret	−0.006	0.063*	−0.004	0.115***	0.002*	−0.005	0.056*	−0.003	0.102***	0.001*
	(0.069)	(0.034)	(0.006)	(0.042)	(0.001)	(0.069)	(0.031)	(0.006)	(0.039)	(0.001)
SP&500 Ret	0.085	0.011	−0.004	0.054	−0.000	0.099	−0.020	−0.002	0.008	−0.001
	(0.087)	(0.017)	(0.005)	(0.042)	(0.001)	(0.087)	(0.017)	(0.004)	(0.040)	(0.001)
Lag Ret Futures	−0.253*					−0.138				
	(0.43)					(0.091)				
Lag Ret diff		−0.085					−0.103			
		(0.117)					(0.112)			
Lag Contango			0.058*					0.057*		
			(0.031)					(0.031)		
Lag Ret diff avg				0.062					0.079	
				(0.103)					(0.087)	
Lag Contango avg					0.078***					0.077***
					(0.002)					(0.002)
Constant	−0.573**	0.162*	−0.080***	0.235*	−0.008	−0.573**	0.171*	−0.082***	0.246*	−0.009
	(0.235)	(0.091)	(0.026)	(0.131)	(0.006)	(0.235)	(0.091)	(0.026)	(0.132)	(0.006)
R-sqr	0.007	0.039	0.132	0.033	0.905	0.006	0.045	0.135	0.039	0.904
Obs	2062	2062	2062	2062	2062	2062	2062	2062	2062	2062

Note: This table reports results from regressions of various daily measures of returns and contango on crowding variables and controls for the period from November 25, 2008, to February 7, 2017. The dependent variables include the first futures returns, the difference between the first futures returns and spot returns, contango, the futures–spot difference computed using the average return of the first 15 futures contracts, and contango in the average first 15 contracts. The crowding variables include the change in daily change in AUM divided by open interest, the weekly ETP flows divided by open interest computed at the daily frequency, and the volume summed across the first 15 futures contracts divided by open interest. The control variables include the daily returns on the MSCI Emerging Market Asia and the SP&500 indices. All the independent variables are standardized. The standard errors of coefficients are listed directly under the parameter estimates in parentheses.

*indicates statistical significance at the 10% using robust standard errors.

**indicates statistical significance at the 5% using robust standard errors.

***indicates statistical significance at the 1% using robust standard errors.

Table 10
Granger Causality Tests.

Indep. Var. \Dep. Var.	Ret fut	Ret diff	Contango	Ret diff avg	Contango avg
	(1)	(2)	(3)	(4)	(5)
	Weekly data without controls				
First PC	0.175	0.000	0.000	0.000	0.041
Second PC	0.304	0.000	0.523	0.006	0.634
# of lags	1	3	2	3	3
	Weekly data with controls				
First PC	0.103	0.000	0.000	0.001	0.000
Second PC	0.672	0.000	0.523	0.009	0.793
# of lags	1	1	1	1	1
	Daily data without controls				
$\frac{\Delta\ \text{AUM}}{\text{OI}}$	0.000	0.000	0.591	0.000	0.000
$\frac{\text{ETP Flows}}{\text{OI}}$	0.000	0.000	0.001	0.000	0.000
$\frac{\text{Volume}}{\text{OI}}$	0.127	0.003	0.000	0.033	0.004
# of lags	3	3	3	3	4
	Daily data with controls				
$\frac{\Delta\ \text{AUM}}{\text{OI}}$	0.000	0.000	0.032	0.000	0.000
$\frac{\text{ETP Flows}}{\text{OI}}$	0.000	0.000	0.003	0.000	0.119
$\frac{\text{Volume}}{\text{OI}}$	0.112	0.002	0.000	0.019	0.023
# of lags	3	2	2	3	2

Note: This table reports the p-values of a Wald test of the hypothesis that the lag values of the crowding measures are jointly equal to zero for the period from November 25, 2008, to February 7, 2017. The variables in the VAR include the crowding variables and either the first futures returns, or the difference between the first futures returns and spot returns, or contango, or the futures–spot difference computed using the average return of the first 15 futures contracts, or contango in the average first 15 contracts. We also consider a specification which includes control variables as additional variables in the VAR. For the weekly analysis, the control variables include the change in U.S. Oil Inventory, the weekly change in overnight repo transactions on Treasury bonds and bills by primary dealers, and weekly returns on the MSCI Emerging Market Asia and the SP&500 indices. For the daily analysis, the control variables include the daily returns on the MSCI Emerging Market Asia and the SP&500 indices. The Schwarz Bayesian information criterion is used to select the number of lags in the VAR.

Table 11
Volatility and Correlation during ETFs First Futures Purchases.

	Vol. Front	Vol. 1st Back	Vol. 2nd back	Vol. 3rd back	Corr. 1st Back	Corr. 2nd Back	Corr. 3rd Back
Intercept	0.170	0.166	0.223	0.240	0.968	0.902	0.820
	(96.182)	(118.678)	(107.202)	(95.529)	(717.285)	(371.454)	(253.684)
ETF first trade dummy	0.063	0.063	0.030	0.009	0.021	0.065	0.106
	(5.214)	(5.352)	(2.113)	(0.652)	(5.348)	(13.186)	(12.441)
With year dummies							
ETF first trade dummy	0.025	0.026	0.029	0.027	0.006	0.019	0.020
	(2.199)	(2.325)	(2.198)	(2.123)	(1.626)	(3.909)	(2.461)
With day of the week dummies							
ETF first trade dummy	0.063	0.063	0.030	0.009	0.021	0.065	0.106
	(5.265)	(5.393)	(2.133)	(0.668)	(5.394)	(13.224)	(12.592)

Note: This table reports the regressions of daily volatility and correlation on a dummy that indicates the first time that an oil ETF purchases a futures contract. The volatility and correlation are computed daily from 5-minutes returns for different futures contracts. The correlation is computed with respect to the front contract. We consider a base regression, one specification that includes year dummies, and one specification that includes day of the week dummies. To save space, these time dummies are not reported. Robust t-statistics are reported in parentheses

Table 12
Exposures of Oil Market to the Fama–French Factors.

Instrument	α	β_{RMRF}	β_{SMB}	β_{HML}	$\bar{R}^2$
Investment Period: 1994–December 2005					
Spot	0.00	0.04	0.25	0.17	0.00
	(1.58)	(0.81)	(3.25)	(1.65)	
Fut1Roll0	0.00	0.04	0.29	0.21	0.01
	(2.48)	(0.81)	(4.21)	(2.25)	
Fut2Roll0	0.00	0.04	0.27	0.18	0.01
	(2.52)	(0.83)	(4.28)	(2.18)	
Fut6Roll0	0.00	0.03	0.20	0.16	0.01
	(2.88)	(0.83)	(4.00)	(2.43)	
Fut12Roll0	0.00	0.03	0.15	0.14	0.00
	(2.77)	(0.86)	(3.58)	(2.50)	
Investment Period: 2006–February 10, 2017					
Spot	0.00	0.63	−0.10	0.07	0.11
	(0.09)	(16.17)	(−1.32)	(1.04)	
Fut1Roll0	−0.00	0.62	−0.08	0.09	0.11
	(−1.05)	(16.66)	(−1.10)	(1.25)	
Fut2Roll0	−0.00	0.62	−0.06	0.13	0.13
	(−1.17)	(17.80)	(−0.94)	(2.01)	
Fut6Roll0	−0.00	0.57	−0.05	0.10	0.14
	(−0.58)	(18.60)	(−0.83)	(1.75)	
Fut12Roll0	−0.00	0.52	−0.04	0.07	0.14
	(−0.38)	(18.83)	(−0.80)	(1.39)	
Investment Period: 2009–February 10, 2017					
Spot	−0.00	0.71	0.07	0.44	0.16
	(−0.17)	(13.96)	(0.78)	(5.15)	
Fut1Roll0	−0.00	0.73	0.07	0.45	0.18
	(−1.20)	(14.87)	(0.80)	(5.48)	
Fut2Roll0	−0.00	0.72	0.08	0.49	0.21
	(−1.46)	(15.76)	(0.97)	(6.46)	
Fut6Roll0	−0.00	0.67	0.08	0.42	0.22
	(−1.04)	(16.66)	(1.16)	(6.31)	
Fut12Roll0	−0.00	0.61	0.08	0.35	0.23
	(−0.99)	(17.28)	(1.26)	(6.03)	

Note: The table presents the exposures of spot oil returns and oil futures returns to the Fama–French factors over three different periods. For each futures contract, the first number indicates the specific futures contract, either 1, 2, 6, or 12, depending on whether the nearest-term, second, sixth, or 12th contract is used. The second number represents the roll date. Thus, a "0" indicates the contract was theoretically rolled on the expiration date of the front contract. The regression is estimated as $r_{it} = \alpha_i + \beta_{RMRF} MKTRF + \beta_{SMB} SMB + \beta_{HML} HML + \epsilon_{it}$, where MKTRF is the equity market return minus the risk-free rate, and SMB and HML are the returns on a value-weighted zero-dollar investment and factor-mimicking portfolio for size and book to equity obtained from Kenneth French's database.

to commodity markets and provide evidence of a shift in the dependence structure between commodities and the stock market in 2008.[39] The commodity markets are therefore becoming more correlated with other traditional asset classes, such as equities. This financialization of the commodity markets might be contributing to crowding in certain areas of the commodity markets.

One way to get an idea of the impact of the financialization of the commodity markets is to examine the exposures of oil to equity factors, such as the Fama–French factors. Table 12 shows the exposures of spot oil, the first, second, sixth, and 12th month futures contracts over three periods, 1994 to 2005, 2006 to 2017, and after the financial crisis from 2009 to 2017.[40] In the earlier period, when contango was not such an issue, oil returns had zero exposure to the market factor. Some of them have exposures to the other factors, but overall, the $\bar{R}^2$ of the

[39] Zhang et al. (2017) is another study that investigates volatility spillovers and co-movements between the equity market and the oil and natural gas markets.

[40] The reader may wonder why the latter two periods overlap. Our main goal is to compare the period prior to 2006 (when oil ETFs began trading) with the period after 2006. However, some readers may have wondered if the financial crisis of 2008 would distort the results. Thus, we added two latter periods, one containing the financial crisis and one not containing it.

regressions is 0. This indicates that generally over the period 1994 to 2005, oil was generally uncorrelated and unrelated to movements in the equity market.

In the second period, 2006 to 2017, the exposures of oil to the equity market were quite large, with point estimates around 0.63 and all statistically significant. To think of it differently, spot oil, in this period, behaved like a company with a β equals to 0.60. The other futures had similar exposures to the equity market. In addition, the $\bar{R}^2$ of the regressions was much higher, at around 0.11. In the final period, 2009 to 2017, the oil market was more exposed to the U.S. equity market, with exposure values ranging from 0.61 to 0.73, and $\bar{R}^2$ values from 0.16 to 0.23. This behavior indicates that something changed between the earlier and later periods with respect to the movement of oil prices, and this change was not driven by the financial crisis period.

Second, we examine whether the oil futures market is now more exposed to scheduled macroeconomic announcements. The surprise components of scheduled macroeconomic announcements have been shown to have a significant impact on stock, bond, and foreign exchange markets (e.g., Andersen et al. (2007)). However, this finding does not transfer to the energy market (e.g., Kilian and Vega (2011)). In an untabulated analysis considering a large sample of 21 macroeconomic announcements used by Balduzzi and Moneta (2017), we run a regression of the front contract futures returns on the standardized surprise component (the announced value minus the consensus forecast).[41] We find that using the sample until 2006, only one announcement (Housing Starts) had a significant impact on oil futures returns at the five percent level. However, when we consider the sample after the financial crisis, we find that six announcements (Federal Open Market Committee rate decision, GDP Price Deflator, Initial Jobless Claims, ISM Purchasing Managers' Index, Philadelphia Fed Index, and Producer Price Index) have a significant impact. This evidence confirms that the oil futures market behaved differently in the last decade. We also examined weekly crude oil inventory announcements from the U.S. Energy Information Administration (EIA). These are oil market-specific announcements, which have been shown to have an impact on oil futures prices (e.g., Bu (2014)). We ran regressions of the returns of the near-term futures contract on the standardized surprise component of the announcement (i.e., announced value minus the consensus forecast) and found a negative impact of those surprise announcements similar to Bu (2014). We also found that the coefficient estimates declined after 2006, compared to before 2006, by about 26% to 34%, depending on the control variables, which is consistent with the idea of the financialization of the commodity markets as oil futures prices respond less to specific oil shocks in the latter period.

Lastly, as an additional test of crowding, we examine whether the correlation between the futures returns with different expiration dates increased in the most recent period. We find that this is the case. For example, the correlation between the front contract and the furthest-back contract increased from 0.82 in the sample until 2006 to 0.93 in the sample after the financial crisis.[42] Further research could investigate whether this increase in correlation is driven by the increase in trading activity by ETFs holding not only the front contracts but also the back contracts.[43]

4. Conclusion

In recent years, investing in oil futures has underperformed a hypothetical benchmark of spot oil, leading to frustration among some oil investors. In this paper, we show that the drag from investing in oil futures is related to contango. We provide evidence that the crowding and financialization of commodities have an impact on futures prices and might contribute to the contango and a distortion of the relationship between oil futures and spot returns. We also provide support that there has been an impact of changes in passive investing capital on futures prices. The futures markets play a very important role in price discovery and price signaling concerning aggregate demand and supply of commodities, which is used by market participants such as producers and corporations using commodities. Sockin and Xiong (2015) provide a theoretical model that highlights that due to informational frictions, investment flow can affect futures prices and feed back to commodity supply and demand and spot prices. Hence, distortions in the futures market, which we at least partially attribute to the increase in capital to oil ETPs, can affect the real economy.

CRediT authorship contribution statement

Ludwig B. Chincarini: Writing of the paper and editing of the paper, retrieving data, loading data, writing different parts of the programming code in STATA and MATLAB. **Fabio Moneta:** Writing of the paper and editing of the paper, retrieving data, loading data, writing different parts of the programming code in STATA and MATLAB.

Appendix A. Data

A.1. Return data

For our empirical analysis of investing in oil, we use daily data from Bloomberg and the CME for WTI oil futures contract prices, volume, and open interest from 1983 to 2017. For our risk-free rate of return, we use the daily return series of the 1-month Treasury bill, which is obtained from Kenneth French's data library. For the spot price of oil, we use the Cushing WTI Spot Price FOB obtained from the Federal Reserve of St. Louis.[44] For our analysis using intra-day data, we obtain data from TickData database, which provides tick-by-tick trade data on the WTI oil futures contracts.

A.2. Crowding data

Measuring crowding in the oil market is difficult because there is not enough detailed information on the types of investors and their actual holdings. In this section, we discuss several data sources that help us potentially identify crowding in the oil markets.

A.2.1. CFTC data — Commitments of Traders data

The Commitments of Traders (COT) data are released every Friday at 3.30 P.M. Eastern and reported based on the most recent Tuesday (with a 3-day lag). This provides a comprehensive and highly configurable graphical representation of the CFTC's report on market open interest, either in aggregated or disaggregated form. Markets are included only if 20 or more traders hold positions equal to or above the reporting levels established by the CFTC and the respective exchanges.[45]

[41] The macro announcements are the following: Advance Retail Sales, Business Inventories, Nonfarm Payrolls, Chicago Purchasing Manager Index, Consumer Confidence, Consumer Price Index, Durable Goods Orders, Employment Cost Index, Existing Home Sales, Federal Open Market Committee rate decision, Gross Domestic Product, GDP Price Deflator, Housing Starts, Industrial Production, Initial Jobless Claims, Leading Indicators, ISM Purchasing Managers' Index, New Home Sales, Philadelphia Fed Index, Producer Price Index, and Unemployment Rate.

[42] In an untabulated analysis, we confirm this increase in correlations when we use intra-day returns data to compute the correlations.

[43] The first oil ETF (USO) was trading only the front contact, but subsequently ETFs that invest in the back contracts were created. For example, DBO is an ETF that minimizes contango by rolling into whichever contract month (within the next 13) looks most attractive by its rules, rather than rolling front-month contracts. Similarly, USL is an ETF that takes a position in 12 different futures contracts instead of investing only in the front contract.

[44] The series DCIWTICO can be found at https://research.stlouisfed.org/fred2. The same data can be found at http://www.eia.gov/petroleum/data.cfm.

[45] For more information, visit https://www.cftc.gov/MarketReports/CommitmentsofTraders/index.htm.

There are four main reports: the Legacy, the Supplemental, the Disaggregated, and Traders in Financial Futures (TFF) markets. The disaggregated reports have the positions of different groups as classified by the CFTC. In particular, positions are classified by producers, swap dealers, managed money, or other. Within the TFF, the positions are broken down into dealer, asset manager, leveraged fund, and other. However, the TFF data do not cover the oil market.

A.2.2. ETP fund flow data

The list of oil ETPs that invest primarily in futures was taken from Bloomberg. To avoid survivorship bias (not accounting for dead funds), we diligently checked ETP Liquidation Watchlist from ETF Global Database from 2013 to make sure no large fund materially affected our results. All oil dead funds have AUM under \$5 million which fell into the bottom 1% of our ETP AUM range. For the daily holding, we obtained data from ETF Global database.

A.3. Other data

In order to control for other variables that might affect oil futures prices, we obtained U.S. Oil Inventory (weekly) from the EIA. We also used the repo transactions on Treasury bonds and bills by primary dealers from the New York Federal Reserve Bank, and the returns on the MSCI Emerging Market Asia and the SP&500 indices from Yahoo Finance.

Appendix B. The computation of rolling returns

In order to analyze and understand the issues related to investing in oil, we must create realistic investing strategies that are available to investors. The most common method to invest in oil is to buy oil futures contracts.

In order to examine the behavior of oil futures investing, we present several strategies. The first strategy is simply to buy a given oil futures contract and choose a rolling strategy as the basis for oil investing. For example, an investor might choose to purchase the front-month contract and roll it to the next contract with five days to expiration. Thus, there will be a strategy for each futures contract chosen, combined with the number of days to expiration chosen as a roll. When we compute the returns for futures investing, we will separate the futures return from the cash return, but also consider them together as if the futures position was fully collateralized. That is, when investors buy \$100 of oil futures, they simultaneously invest \$100 in Treasury bills. Thus, the total return will include both.[46]

We compute rolling returns for various futures contracts with various roll dates. That is, if we consider the near-term futures contract (i.e., the futures contract closest to expiration on any given day) and we chose a 10-day roll, then 10 days before the nearest futures contract expires, we compute the strategy of selling it on that day and buying the next nearest contract. For our computations, we assume that these trades occur using the closing prices of the contracts. We use the following notation. F_t^1, F_t^2, F_t^3 represent on day t the price of the first, second, and third nearest maturing futures contract. Our rolling strategy is based on business days rather than actual days. On the roll day, we sell all the contracts at the closing price and we buy the new contracts at the closing price. The returns from rolling the futures contract over k-days is given by:

$$r^i_{t,t+k,d} = \frac{F^i_{t+k,d,m-k}}{F^i_{t,d,m}} - 1. \tag{6}$$

where i represents the contract number, d represents the roll period, m represents the days to maturity or expiration of the contract, and F represents the futures price.

[46] In actual futures investing, only about 95% is invested in Treasury bills due to margin requirements.

Appendix C. Performance attribution

In order to understand the sources of return of the futures investment strategy, one can decompose the return series into two components. If one initiates a purchase of a futures contract, i, on day t, then the return from day t to day $t+k$ is given by:

$$r^i_{t,t+k,d} = \frac{F^i_{t+k,d,m-k}}{F^i_{t,d,m}} - 1 = \underbrace{\frac{F^*_{t,d,m-k} - F^i_{t,d,m}}{F^i_{t,d,m}}}_{\text{“Expected Roll”}} + \underbrace{\frac{F^i_{t+k,d,m-k} - F^*_{t,d,m-k}}{F^i_{t,d,m}}}_{\text{“Spot Return”}} \tag{7}$$

where $F^*_{t,d,m-k}$ is the price of a synthetic futures contract that has $m-k$ days to maturity on day t, $F^i_{t,d,m}$ is the price of the futures contract i on day t with the roll performed d days prior to expiration and a maturity or expiration in m days, and $F^i_{t+k,d,m-k}$ is the price of the same futures contract after k days. The "Expected Roll" is also sometimes called the carry of the trade. It represents the percentage return from rolling the futures contract over k days, if the futures curve remains constant. Thus, in this sense, it is the expected roll. The Expected Roll is driven by the term structure of futures prices and therefore it depends on the components of the cost of carry (interest rates, storage costs, and convenience yield). The "Spot Return" represents the change in price of the futures contract along the futures curve after k days. This is the portion of the return due to movements in the price of oil.[47]

A similar decomposition is presented in other papers (e.g., Erb and Harvey (2006)). The difference is that we use a synthetic futures price F^*. In practice, the security price $F^*_{t,d,m-k}$ does not exist. In order to calculate this price, we perform a very simple linear interpolation of futures prices between the spot, the first future, and so on.[48] Thus, for the nearest-term future,

$$F^{1*}_{t,d,m-k} = \frac{F^1_{t,d,m} - S_t}{m} \cdot k + S_t \tag{8}$$

where m represents the number of days until the first futures expires.

The excess return and tracking error with respect to spot oil and our adjusted oil benchmark is given by:

$$\begin{aligned} xr^i_{t,t+k,d} &= \left(\frac{F^i_{t+k,d,m-k}}{F^i_{t,d,m}} - 1\right) - \left(\frac{S_{t+k}}{S_t} - 1\right) \\ &= \underbrace{\frac{F^*_{t,d,m-k} - F^i_{t,d,m}}{F^i_{t,d,m}}}_{\text{“Expected Roll”}} + \underbrace{\frac{F^i_{t+k,d,m-k} - F^*_{t,d,m-k}}{F^i_{t,d,m}}}_{\text{“Spot Return”}} - \left(\underbrace{\frac{S_{t+k}}{S_t} - 1}_{\text{Spot Return}}\right) \end{aligned} \tag{9}$$

$$T.E. = \sqrt{\mathrm{Var}(xr^i_{t,t+k,d})} \tag{10}$$

where the return of the spot can either be our new benchmark of spot index minus storage costs or the regular spot index.

In addition to the period-by-period attribution, it is often interesting to examine the cumulative behavior of the futures rolling program. That is, over a given period of time, how much of the total return of the futures was due to changes in the "spot" rates and how much was due to the contango or backwardation of the market. In order to examine this, we use Eq. (9) above and call the first term r_{roll} and the

[47] It is called spot returns, although spot prices are not used. The assumption is that futures price is a good proxy of spot price. Furthermore, a return from investing in the spot market should include any cash flows associated with holdings the position.

[48] There are much more sophisticated ways to deal with this, but our purpose is simply to obtain a general idea of the different components of return from rolling futures contracts. We also interpolate from the current futures price to the spot price using days until futures expiration. In reality, oil futures expiration occurs 10 to 14 days before the first physical delivery of the oil. For another discussion on this topic, see Erb and Harvey (2006).

second term r_{spot}. This is not to be confused with the return of spot oil. We can then calculate the cumulative effect of either component as an adaptation of Frongello (2002). That is,

$$r_{roll}^{1,N} = \sum_{i=1}^{N} r_{roll}^{i} \prod_{j=1}^{i-1}(1+r_j) \tag{11}$$

$$r_{spot}^{1,N} = \sum_{i=1}^{N} r_{spot}^{i} \prod_{j=1}^{i-1}(1+r_j) \tag{12}$$

where $r_{spot}^{1,N}$ represents the cumulative return of the spot component, $r_{roll}^{1,N}$ represents the cumulative return of the roll component, r_j represents the actual futures returns in period j, and the cumulative returns are computed over the N sub-periods of concern.

The reader will note the convenience of this formulation, in that, the cumulative return of the futures rolling, $\prod_{i=1}^{N}(1+r_i)-1$, equals the sum of the cumulative effect of the roll and spot components. Thus, $r_{roll}^{1,N} + r_{spot}^{1,N} = \prod_{i=1}^{N}(1+r_i)-1$.[49]

Appendix D. Measurement of contango or backwardation

In order to measure the actual contango or backwardation of the futures curve on day t, we define the contango or backwardation by:

$$C_{t,d}^{i} = F_{t,d,m}^{i} - F_{t,d,d}^{*} \tag{13}$$

When this value is negative, the futures curve is said to be in backwardation. In order to get the contango in percentage terms, we divide our contango measure by $F_{t,d,m}^{i}$. In order to obtain annualized percentage contango, we divide our percentage contango into the number of days until the roll, and then multiply that by 250.

In our empirical analysis, we roll at the expiration of the front contract (d equals to zero), and the formula for contango becomes[50]:

$$C_t^i = \frac{F_{t,m}^{i} - S_t}{F_{t,m}^{i}} \frac{250}{m} \tag{14}$$

Appendix E. Difference between futures and spot returns

According to the cost-of-carry no-arbitrage relation, the futures price is

$$F_{t,m}^{i} = S_t e^{\Psi_t m} \tag{15}$$

where the cost of carry $\Psi_t = r_t + u_t - y_t$ and r is the interest rate, u is the storage cost, and y is the convenience yield. Note that the cost of carry can be estimated using the slope of the term structure as:

$$\Psi_t = \ln\left(\frac{F_{t,m}^{i}}{S_t}\right)\frac{1}{m} \tag{16}$$

This is closely related to the non-annualized measure of contango (the difference is in the denominator).

Bessembinder et al. (2016) show that the difference between the one-period return to a long position in a given futures contract and the continuously compounded growth in the spot price ($r_{s,t} = \ln\left(\frac{S_t}{S_{t-1}}\right)$) can be written as (see equation A4 minus equation A5 on page 165 of Bessembinder et al. (2016)):

$$r_{f,t} - r_{s,t} = (m-1)\Delta\Psi - \Psi_{t-1} = m\Delta\Psi - \Psi_t \tag{17}$$

where $\Delta\Psi = \Psi_t - \Psi_{t-1}$. Hence, the difference between the futures and spot returns depends on the cost of carry (measured by the slope of the futures term structure) and its change. The drivers of this difference are then the components of the cost of carry: the convenience yield, the interest rate, and the storage cost.

[49] For the simple 2 period case, the left-hand side equals $r_{roll}^1 + r_{roll}^2(1+r_1) + r_{spot}^1 + r_{spot}^2(1+r_1) = r_{roll}^1 + r_{spot}^1 + r_1(r_{spot}^2 + r_{roll}^2) + r_{spot}^2 + r_{roll}^2 = r_1 + r_1 r_2 + r_2 = (1+r_1)(1+r_2) - 1$, using the fact that $r_{roll}^i + r_{spot}^i = r_i$ by definition.

[50] Other papers (e.g., Gorton and Rohwenhorst (2006)) use the difference between the price of the front contract and the next nearest contract to compute a measure of contango instead of the difference between the price of the front contract and the spot price. The reason is that for some commodities, spot prices are not available or are unreliable. We tried to use this approach and we obtain similar results.

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