Sticky Backwardation? Profiting in the Oil Futures Market

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Abstract

Since 1970, there have been four major price shocks in the market for crude oil. The futures market, where price is set now for delivery later, was created after the first two price shocks to allow producers and importers to hedge expectations of supply and demand. A shift in the slope of the crude oil futures curve to where far month futures contracts trade at a lower price than the near month futures for a sustained period during shocked prices, labeled here "sticky backwardation", is found to provide an entry signal into a leveraged short trading strategy that profits from both the 2008 and 2014 crude price crashes.

1.0 - Introduction

Crude oil is a collection of hydrocarbons in liquid form below the surface of the earth. In this raw form, it is largely unusable without refinement into a variety of petroleum products, which can be seen as the derivatives of crude oil that go into cars, jets, and homes. Petroleum is a broad category that encompasses both crude oil and petroleum products - sometimes *oil*, *petroleum,* and *crude* are used interchangeably.

Short term crude oil prices are determined by a well-defined set of factors, popularized in 1991 by ARCO1, a Bayesian belief network.

ARCO1 deconstructed the supply and demand fundamentals of the oil market into quantifiable input terms to produce a short term expected price for oil. Expansions of this model are used to this day to trade around regularly released supply data points. The key contribution of ARCO1 was its ability to categorize the influences of short term price at an intersection of interdependent expectations of demand and supply fluctuation.

A negative supply shock is when a producer of a given product decides to cut production, shifting supply left to meet demand at a higher price. There have been multiple negative supply shocks in the crude oil market over recent history.

A future is when price is set now between buyers and sellers of a given product for a delivery in the future. For example, say Nigeria has 100 barrels of crude oil in storage. Nigeria can agree to sell Britain 100 barrels of crude oil at a price determined now for a delivery 9 months into the future. Britain will pay now and receive a futures contract, issued by Nigeria, that promises Nigeria will deliver the oil on the specified date. Nigeria is "short" the futures contract, as the seller, and Britain is "long" the futures contract, as the buyer.

Prior to the creation of the crude oil futures market in the 1980s, spot contracts were the only way to trade crude oil. Like any traditional market, buyers and sellers agree on price and volume at the present time and exchange the oil between parties. In 1983, NYMEX and CBOT first opened up futures trading for oil contracts, allowing deliveries at a fixed price and volume to be made at a specified point in time out in the future.

The creation of a futures market serves many purposes. Arguably the most important one is the ability for exporters to hedge the sale of their product. For example, a given country can promise the sale of a million barrels of crude to be executed one year into the future at a given strike price per barrel. If crude is trading below the futures strike price, the hedge was a smart decision, and in the case that crude rallies above the futures price, the export nation must sell at the strike and miss any extra profit from selling those barrels on the spot market. However, the futures market still enables producers to pay a premium for price security and thus the futures market reflects the expectations of the oil traders.

Much work has been done regarding the role that futures play in determining spot prices and vice versa. First, the notion that prices follow a random walk is not true in the case of crude oil futures. Gülen (1998) and Silvapulle (1999) both concluded that futures prices have at least some degree of "price discovery" associated with them so futures prices might not be perfectly priced at any given moment. Further, prices in future time periods are a function of prices in the current time period, so the futures price exhibits autocorrelation.

When the spot price of oil spikes as result of a supply shock, the futures curve follows. Often it is not clear how long or how severe any given shock will be, thus pricing futures during a supply shock becomes a precarious task (Yergin 2011). The near month (one month out delivery) future should move identically with spot price, as this future only captures one month of storage costs and changes in supply or demand expectation. If the far month (nine months out delivery) future is priced higher than the near month future, the market is said to be in *contango*. Expectation has deemed prices should trend up. On the contrary, when the far month future is priced lower than the near month, the market is said to be in *backwardation* and the market is expecting prices out in time to fall (Considine, Larsen 2001)

Examining levels of contango and backwardation between futures time spreads during periods of shocked prices provides insight into how changes in expectation of future spreads can be used as entry, exit, and leverage signals in a trading strategy that profits from a phenomena found in the spread deemed "sticky backwardation."

Chicago Mercantile Exchange (CME) Crude Light (CL) Oil Futures daily prices during the time period 01/02/2007 and 03/01/2017 are examined for the following reasons:

- The decade captures two periods of shocked prices as a result of supply disruption
    - 2008: Bottleneck in refining capacity
    - 2011-2013: The Arab Spring
- The decade captures two periods of post-shock depressed prices

  - 2008: Global financial crisis
  - 2013: Overproduction by Saudi Arabia and surging U.S. production
- Both previous shocked price periods occurred in the 1972 and 1978, prior to the creation of a liquid futures market
- Technological change between 2007 and 2017 is dramatic and well-documented. The shale and fracking revolution in the U.S, the rise of the economically efficient solar panel, and the rise of the electric vehicle are a few of many trends that have changed the perceptions and position of crude oil within the modern economy and presently show no sign of slowing.
- The time frame starts and ends at the same real oil price, around $50 per barrel, the historical average cost of producing one barrel of crude since the 1970s.

The goals of the work can be divided as follows: Establish a historical context for oil supply and price shocks, explain the motivations behind the shocks in the past decade, identify how producer order flow fits into these periods of shocked price, and finally, identify a trade signal in futures prices that reflects this order flow and which can enter, leverage, and exit a position in the futures market during shocked prices.

2.0 - History of the Main Drivers of Oil Price Changes

Before exploring the shocks of the 21st century, knowing something about the history of prior crude oil supply shocks for perspective and motivation behind the the trading algorithm is worthwhile. Note all prices are nominal unless noted otherwise.

The first modern supply shock, the oil crisis of 1973, was unexpected and costly. In January, 1973, the Shah of Iran announced that an agreement between Iran and a number of largely American and Dutch oil companies would not be renewed after its expiry date in 1979. At the same time, the U.S. was coping with a severe winter and shortage of heating oil as a result of declining U.S. oil production, partly as a product of saturated petroleum refinery capacity. OPEC discussed raising the price of oil to counteract the falling value of the U.S. dollar, a relationship explored later for the trading algorithm.

On October 6th, the Arab-Israeli War of 1973, also known as the Yom Kippur War or Ramadan War, began with a coalition of Arab states led by Syria and Egypt fighting against Israel over territory in the Sinai and Golan Heights regions. The following day, Iran nationalized all Exxon and Mobil shares in the state run Basrah Petroleum Company.

Nixon requested $2 Billion from Congress for immediate Israeli aid. The Arab states realized that the oil weapon must be used to combat U.S. foreign aid and therefore imposed an oil embargo on the allies of Israel, namely the U.S. and Netherlands. By November, the Arab producers announced a production cut of 25%. In December, they announced a hike in posted crude price from $5 to $11 per barrel. Within 3 days of the announcement crude traded at nearly $12 per barrel, quadruple from earlier in the same year (Yergin 2011).

If 1973 is considered the year of the shock, 1974 can be considered the response to such a chain of events. Israel pulled soldiers from the Suez Canal, the embargo ended in March, equity markets stabilized, and import nations dependent on Persian Gulf started protecting themselves from future shock events. Nixon announced the launch of "Project Independence", an initiative to make the U.S. a self-sufficient energy nation by 1980, by attacking the problem of energy dependence from two angles: reduced consumption and development of alternative energies. Reduction of the national highway speed limit, conversion of oil power plants to coal, the Trans-Alaskan Pipeline, increased investment into mass transit, and plans to construct 1,000 nuclear power plants by 2000 were some of the many specific policy goals of the initiative. However, as detailed in the next section, this initiative set lofty expectations it could not meet. The US Strategic Petroleum Reserve was founded in 1975 (Yergin 2011).

The second oil shock occurred in 1979 and was somewhat less unexpected than the previous shock but still significant nonetheless. Compared to the volatile international politics of the 1973 shock, this shock resulted from the aftermath of the Iranian Revolution and the Iran-Iraq War. Iranian production dropped heavily, causing oil to spike to nearly $40 per barrel.

With the drop in Iranian production, global supply receded a mere 4%, which industry experts agree should not have caused an oil price shock (Parrilla 2015). Nonetheless, the bitterness of the previous shock combined with a lack of a futures market to enable long term hedges contributed to a market-wide panic.

2.1 - The First Post-Shock Oil Market

Following the sharp spike in price, an initial sign of the production scarcity ending occurred in November 1980 when the first attempt at peace was unsuccessfully brokered between Tehran and Baghdad. One month later, OPEC agreed to post $36 per barrel but Saudi Arabia decided to post $32 per barrel, undercutting their fellow monopoly peers by showing no regard for the established pricing agreement. Over the next 11 months, the Saudis flooded the market with their cheaper oil, forcing the rest of OPEC to either cut prices or see demand diminish.

By October 1981, all of OPEC was forced to post $32 per barrel through 1982. During that same time period, a second attempt at brokering peace between Iran and Iraq failed. Early in 1982, the global market realized the number of producers attracted to the price of crude were inflating supply. Indications of a global supply glut pushed prices lower, and OPEC appeared to lose its grasp on global oil prices for the first time. In 1983, following a drop in demand resulting from recession, energy conservation, and use of other fuels, OPEC agreed to individual output quotas and cut prices further to $29 per barrel (Yergin 2011).

1983 was also the year The New York Mercantile Exchange (NYMEX) and Chicago Board of Trade (CBOT) opened oil futures trading contracts. The creation of a futures market dampened uncertainty, as oil traders could position themselves to take or offload inventory in the future, lessening the impact of shock events by providing a hedge. In 1984, Britain, Norway, and Nigeria slashed prices on futures contracts in response to OPEC overproduction. For the first time in history, futures prices traded at a discount to spot prices, called backwardation. Physical order flow in the market anticipated a fall in prices.

Later in 1984, OPEC finally announced production cuts but the cuts were useless as many members simply ignored the limits and others posted price-discounts. In early 1985, a developing discrepancy in price between heavy sour and light sweet[1] crude formed as a result of light sweet players entering the market to undercut OPEC, forcing OPEC to cut prices further to narrow the price gap between the two grades. OPEC continued to post lower prices as it loses customers to cheaper North Sea oil (Parrilla 2015). In August 1985, Saudi Arabia choose to link their posted prices with the spot market causing Saudi output to more than double over the next half year. By December, 1985, OPEC net output ballooned, promoting a massive supply glut and triggering a price war (Yergin 2011).

A perfect collection of factors had come together since the peak of the second shock in 1980 that promoted a supply glut and reduced the inelasticity of demand for oil. High prices attracted exploration in Siberia, Alaska, the North Sea, and the Gulf of Mexico. The Soviet Union became the world's largest producer of oil. The impact of smaller, non-OPEC countries became formidable. Countries like Oman, India, and Malaysia doubled output between 1980 and 1985. Brazilian ethanol proved to be a viable alternative to crude oil (Parrilla 2015). The Trans-Alaska Pipeline outlined in Nixon's Project Independence combined with reduced taxes on profits generated by oil companies during a price spike (reduced windfall taxes) and free-market prices as a result of the elimination of price controls prompted an increase in US oil production. One notable field developed at this time, the Prudhoe Bay Oil Field in Alaska, contributed a quarter of all US production in 1988. Phillips Petroleum made large oil discoveries in the North Sea, prompting a flurry of exploration and investment by a number of companies trying to drill a piece of the Norwegian continental shelf (Gately 1986).

As a result, the oil price crashed in 1985. This excerpt from Dan Gately before the 1986 OPEC Convention accurately reflects the above and offers insight into the mentality of OPEC leaders and academics at the time of this crash:

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[1] Oil comes in two grades, heavy sour and light sweet. Heavy sour is found mostly in Saudi Arabia and other OPEC Persian Gulf countries while light sweet is found elsewhere, generally west, such as the United States, Canada, and the Norwegian Continental Shelf. The difference in the grades corresponds to the sulfuric content in the crude oil, with heavy sour containing more sulfur and thus requiring a more intensive refining process while light sweet is relatively sulfur-less. Usually the two grades trade within a narrow spread, but sometimes that spread widens as seen in 1984 and 2008.

> "The 1986 price collapse was the result of a decision by Saudi Arabia and some of its neighbors to increase their share of the oil market. Unlike other producers, they did not suffer great revenue losses, because the price declines were offset by their output increases…By no means does the 1986 price collapse represent the death of OPEC...
>
> …Over the next two decades, price can be expected to increase substantially, although OPEC will continue to have difficulty restricting output if it raises price too far above what is warranted by market conditions. The world's oil resources are still heavily concentrated in the Persian Gulf, and there is no alternative energy source now on the horizon that is cheap, clean, and plentiful…the demand for OPEC oil will grow substantially, and OPEC will respond by raising the price. But OPEC, especially Saudi Arabia and its allies, will probably be cautious in the future about abrupt price increases, having seen the consequences during 1980-86." - Dan Gately, 1986 OPEC Convention

Aside: Depressed Price in the 1990s and the Saddam Shock

The oil market themes for the rest of the 1990s into the 21st century follow much of Gately's thinking above - producers began taking positions in as much oil as possible because it was a lasting, lucrative endeavor. Competition was endogenous to the oil market, there was no clear substitute in sight, and OPEC had the greatest concentration of the resource in the world. Nonetheless, the price did not steadily increase over the next 15 years as Gately predicted. Sans output disruption, the flock of producers attracted to the price action of the two previous shocks motivated glutting supply, despite a negligible brief price shock as a result of Saddam Hussein leading the Iraqi invasion of fellow OPEC member Kuwait in 1990. Supply overexpansion combined with demand destruction events such as the Asian economic crisis of the late 1990s depressed prices for the 15 years following 1985 (Yergin 2011), but it would not be long before the next price shock occurred.

2.2 - The 2000s

On January 02, 2007, global economic fundamentals were sound. Equity markets were performing well, inflation was steady, crude oil was trading near $50 a barrel and the market was in slight contango (far month futures price higher than near month futures price) across the 1, 3, 6, and 9-month time spreads. Demand growth was promising, with Asian powerhouses like China posting double digit growth year over year.

The reason oil prices rose so sharply headed into 2008 was a bottleneck in the refining capacity of heavy sour crude (Parrilla 2015). Oil inventory data indicated plenty of heavy sour crude supply, however, there were not enough refineries to process it into the inputs that go into cars, jets, and homes. Industry experts cite numerous reasons as to why this discrepancy arose in the first place, largely overlapping on citing lack of accurate demand growth forecasting due to the Asian boom, intricacies in inefficiency due to the location of refineries relative to the extraction and delivery points of the crude, and lack of price incentive to produce refineries that could alleviate the bottleneck before it creeped up. Regardless, since demand for oil was strong and governments were willing to subsidize price spikes, the market was willing to pay a higher price for the same refined product. To make matters worse, since the refineries could not accept any heavier sour crude, Saudi Arabia was forced to cut production of their own heavy sour crude to meet this demand at a lower point, further driving up the price of refined products. By July 2008, oil was pushing $140 per barrel (Parrilla 2015).

The difference in demand between heavy and light grades of crude incentivized the creation of "upgrading" refineries to convert heavy oil into light oil. These refineries were efficient and built quickly, during a rare period in crude history when the refiners, not the producers, gained the power over price (Parrilla 2015).

The other major contribution to prices at this time was a set of government subsidies. Governments, especially those in the East, would subsidize oil imports so their citizens did not face the burden of shocked prices. This made consumers addicted to cheap prices and transferred the burden of any price spikes to the government. As governments began to realize they could not afford the subsidies, they were put in a difficult position deciding between cutting the programs, causing unrest and inflation, or running a deficit (Yergin 2011).

The price came crashing down when a massive global credit bubble burst, triggering the global financial crisis. OPEC aggressively cut production to meet the drop in demand to successfully catch oil prices just above $30 per barrel. Over the following months, the economy and oil prices stabilized and recovered. However, a geopolitical price shock approached shortly.

2.3 - The Arab Spring

Starting in late 2010, protests fueled by social media such as Twitter and Facebook gained traction across North Africa. The general theme remained consistent across the protests: Arab youth and progressives were not satisfied with historically oppressive regimes exerting unconstrained power. Mubarak, Assad, and Gaddafi all faced uprisings in Egypt, Syria, and Libya, respectively. Mubarak was ousted in February 2011. By March, most of Libyan oil output had come to a sharp halt. Deep production cuts were expected to remain for the foreseeable future, encouraging the far month futures markets to trade at premium. The Syrian Civil War introduced uncertainty in the market as well. The spread between the nine month and one month CME crude light future shifted drastically intraday, reflecting this uncertainty with volatility. The release of 60 million barrels of oil from the Global Strategic Petroleum reserves helped alleviate some of the disrupted output, however, prices remained shocked at $100 per barrel headed into 2014 (Parrilla 2015).

2.4 - 2014 Oil Crash

By Q4 2014, oil had crashed from over $100 to $55 per barrel. There was plenty of geopolitical risk at this time, with ISIS being a growing concern and taking numerous cities in Iraq, including Mosul. However, they left the Kurdish oil fields north of the Iraqi border intact. Though ISIS presented a geopolitical threat, they were deemed a low risk for disrupting supply. At the same time, OPEC could not function properly as a cartel. As prices crashed, production ramped, snowballing a self-reinforcing downward feedback loop. Members could not agree upon production cuts, as it was simply too easy to cheat. Saudi Arabia made it clear it would continue producing despite the crash in prices, possibly interpreted as a strategy to drive away U.S. production attracted to high prices and gain market share in growing markets such as China from threatening competition like Russia. Simultaneously, the U.S. began to make it clear that it was on a path to technology driven self-sufficiency. Rapid advances in shale oil discovery and drilling combined with natural gas finding its way as a substitute in more places, like heating homes in the Midwest, proved to decrease U.S. thirst for foreign oil. Discoveries in areas such as the Permian Basin in Texas also proved domestic supply would last into the future regardless of demand, a strong step towards self-sufficiency (Morse 2014). On the demand side elsewhere, growth did indeed wane in China, Japan, and Europe compared to expectations, however, the 2014 crash was undoubtedly driven by supply. Geopolitical risk no longer reigned over the fundamentals of supply and demand, sending prices crashing (Blackwill 2014). As of May 2017, prices have yet to recover significantly from this shift towards glutting supply, slowing oil demand, and surging U.S. production.

3.0 - Trading Strategy Principle

The first of the four major oil price shocks represented a shift in the market to a new normal level for price until the next shock. Note all prices in this section are real prices in 2015 U.S. dollars unless otherwise noted.

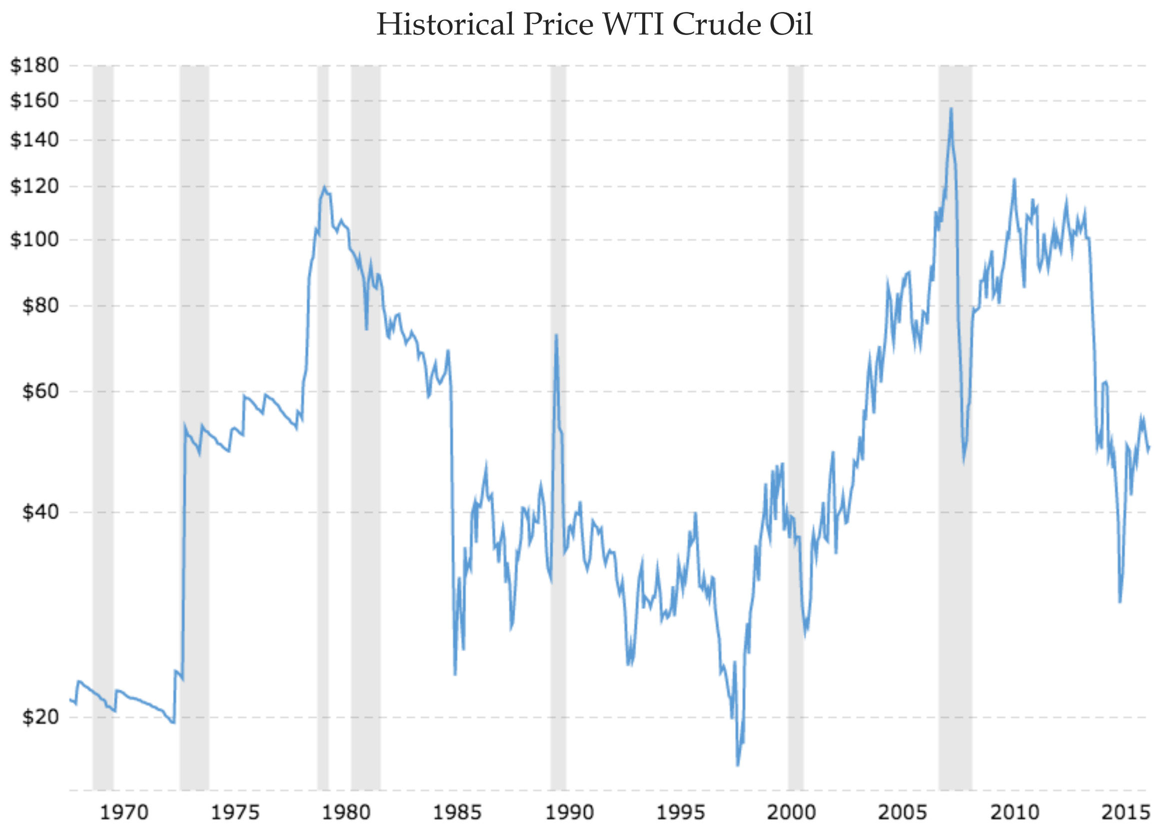

Figure 1: WTI Crude Oil Historical Chart 2015 Adjusted Prices - Grey bars indicate recession, Macrotrends.net

After price was shocked in 1974 to the $50-$60 range, it remained in that range until it was shocked once again to an unsustainable high of $120, and then gradually recovered back to the $60 level prior to the crash of 1985. The historical average cost of producing a single barrel of crude oil, averaged across producers, since the 1970s, has held nearly constant averaging about $50 per barrel, depending on the source (EIA, Bloomberg, Parrilla 2015, Yergin 2011). Arguably, the 1972 oil price shock was necessary, as it established that the prices prior to the shock were too low for producers' costs. The 1985 price crash reflected producers' attraction to this shift towards relatively high prices, with capital investment, upstream exploration, and production promoting a glut in supply that sent prices crashing.

In "The Energy World is Flat", Diego Parrilla references "The World is Flat" by Thomas Friedman, which explores globalization in the early 21st century. Regarding the dotcom bubble at the turn of the century, Friedman argues that soaring valuations in internet companies drove investment into infrastructure which helped spread the internet around the world cheaply and rapidly. Once internet infrastructure is built, such as a server for example, it has a multi-year operable lifespan. When valuations soared during the dotcom bubble, internet infrastructure was built on unsustainable expectations but when the bubble crashed, the infrastructure still existed. Parrilla applies the same logic to the oil industry during the first two price shocks to explain that producers were attracted to the prices after the first two shocks and thus flocked to create infrastructure, such as deep-water rigs in the North Sea, on unsustainable expectations of price. When that price came crashing down as a result of too many producers entering the space by 1985, the infrastructure built over the previous decade was there for years to come. So the sustained period of depressed prices after 1985 reflects a boom in infrastructure promoting cheap oil as demand lagged supply. Similar to internet in the dotcom bubble, the first two oil shocks actually promoted cheaper oil price in the aftermath of the shocks. Parrilla argues oil price shocks can actually be viewed as a deflationary force on the price of oil by the logic above.

The culmination of this historical perspective combined with the views expressed by Parrilla and Freidman motivate the construction of a trading strategy that is exclusively short oil futures, employing the philosophy that shocked prices must be unsustainable for prolonged periods and producers with industry knowledge will hedge their product in anticipation of falling price.

Trading commodity futures differs from trading traditional instruments, like stocks, in many ways. If a trader expected the price of a stock to eventually fall, the trader can short the stock and hold the position until the stock eventually falls. Unlike stocks, futures expire on a certain date and time, incur the cost of storage, and face a cost to rollover if delivery is postponed. These concerns are addressed in the following section.

3.1 - Order Flow in Crude Light Futures

Physical traders have a tangible stake in the market as a result of being producers, storage holders, transporters, or anything that requires physically holding oil at some point. Speculators are those who simply trade futures but never take or provide delivery for the contracts, either by rolling the contract over or selling / buying to cover before expiry.

If a speculator were to purchase a contract for delivery of crude oil one month out from today, as that date approaches, the speculator would decide to either sell the contract to another trader or “roll” it over to the next month. To simplify the roll, when a speculator decides to postpone delivery of a long futures position, there is a cost associated with pushing the delivery back out in time. Similarly, if a speculator is short a futures position, as that date approaches, the speculator can either close the position by buying to cover the contract before expiry, or they can roll the short position over out in time and say they will provide delivery later. The latter case on short contracts incurs a cost of rolling that future. Given the costs of rolling futures, the trading strategy employed should buy to cover the short position before expiry, to avoid the cost of roll. In other words, the maximum amount of time that the algorithm can be short any given futures contract is less than the time to expiry from the date the contract is purchased.

There has been significant work addressing the role of speculators versus physical traders in futures markets and the results are conclusive: physical traders drive prices while speculators are along for the ride (Kilian and Murphy 2014, Harris and Büyükşahin 2011). The prices in the spot market for crude oil are certainly driven by physical traders, as the spot market is physical in its very nature of immediate transfer of ownership. When futures markets were first introduced, many argued that speculators were responsible for driving prices out in time but that notion turned out to be false, as physical traders traded out in time just as they would in the spot market, and thus are the price drivers in the futures market. Recall that Nigeria sold futures prices prior to the crash of 1985 in response to the expectation that Saudi Arabia would continue overproducing. Nigeria was the physical trader driving order flow in that futures price based on industry knowledge and risk constraints, as the futures sale was a perfect hedge against the falling price.

3.2 - Abnormal vs. Normal

From the history above, it is argued that the factors which motivate price to move up to shocked levels are abnormal events, which are difficult to predict and largely unexpected. For example, a bottleneck in refining capacity or the Arab Spring can be viewed as abnormal events.

Shocked levels can be considered anything at or above twice the approximated cost of producing a barrel of crude oil, which has historically been holding an average at approximately $50 per barrel (inflation-adjusted) since 1970. Thus, in the time frame of this work, the two shocked levels would be the refining bottleneck and the Arab Spring.

When examining the futures curve over time, slight contango is considered normal. Far month futures should be systematically priced slightly higher than near month futures to account for the cost of storage.

Consider a scenario where the far month future is priced significantly higher, exceeding the costs of storage, than the near month future. Such a scenario allows traders with physical storage to arbitrage profit by simultaneously buying the near month future for delivery and selling the far month future for delivery. The trader takes the delivery of the oil in the near month, stores the oil, and provides delivery in the far month to capture the difference in the spread. Such a contango trade is profitable when prices crash and expectation dictates they should rise in the future. For example, after the crash of 2014, major commodity trading houses such as Trafigura posted the best trading profit results in years due to severe contango following the crash in prices. However, as more traders with more storage see this opportunity, they will sell that far month future continuously, regressing the futures curve back to the slight contango equivalent to the costs of storage and ensuring that contango arbitrage profit is diminished. Absent a bottleneck in storage capacity, high levels of contango should not be sustainable for significant amount of time but a slight contango can be considered “normal” (Alquist and Kilian 2010). When far month futures are priced lower than the near month, backwardation, the market is in a state of abnormality. The fundamentals of supply and demand dictate that a far month future price will be trading lower than a near month future price only if there are sellers pushing that price to such a level. Despite the costs of storage, there are traders willing to sell that far month future because they believe prices will fall. Since it is established that speculation is secondary to the physical flows in the market, it is reasonable to conclude that when the market backwardates, there is at least some order flow in the market locking in a hedge against price falling further in the future. This order flow can come from producers, market players with large amounts of stored crude and forward-looking insight into the expectations of supply and demand. Futures markets were largely designed to provide physical traders with hedges so when the market is in backwardation, there must be more physical traders willing to sell rather than purchase the far month contract, driving price below near month levels.

3.3 - Sticky Backwardation

Keeping this order flow in mind, when the slope of the futures curve between the 1-month and 9-month future shifts from positive to negative, the market slips from a state of contango to backwardation, which is a state of normalcy to a state of abnormality. If the negative slope persists for a sustained period, there are more physical traders selling the 9-month contract than purchasing, which is another way of saying physical traders are continuously hedging their inventory against a fall in prices while the bidders on the contract are all getting filled or pulling their orders, driving the supply for the contract higher than the demand.

Using the shift of the futures curve from a period of contango to a sustained period of backwardation thus gives an indication of entry into a state when physical traders expect prices to fall or rise over the course of the next 9-months. Further, if the period of backwardation is sustained, traders are consistently expecting prices to fall and are taking out hedges against their product every single day. The logic then follows that the longer the backwardation persists in the market, “sticky backwardation”, the more likely it should be that the market actually does come down, as physical traders with industry knowledge are willing to bet their money on prices crashing day after day.

This gives the motivation behind the following pseudocode:

```
For each trading day examined (
If CL1CL9² is in contango (positive):
      Append 1 to the contango tally
If CL1CL9 is in backwardation (negative):
      Reset contango tally to zero
      Append 1 to the backwardation tally
If the backwardation tally is greater than some fixed constant:
      Short CL9 leveraged as linear function of periods presently in
backwardation
      Purchase something that should rise from a fall in crude prices
If the contango tally is greater than some fixed constant:
      Close position on anything purchased that should rise from a fall
in crude
      Stop shorting futures
)
Notes:
   -  Reset all parameters after the algorithm completes a trade cycle
```

The pseudocode begs some explanation and choices. The spread CL1CL9 is chosen because it is the widest spread available in the dataset but also sensible. Historically, price shocks have lasted anywhere from 2 to 3 years so CL1CL9 being 9-months out captures the most time for prices to regress towards an anticipated fall in futures price. In other words, the widest spread within one year is ideal because as mentioned, the algorithm must cover the futures position before expiry to avoid the cost of the roll and thus CL1CL9 provides the most time between when the future is purchased and when the algorithm will cover the short.

Next, the constant chosen to identify sustained backwardation and contango in the market. Given the 2,567 trading days over the past decade and since the strategy is run on daily prices, implying the holding time is multiple days, choosing a reasonably large constant is necessary. The constant chosen should identify periods of sustained backwardation during the 2008 and 2013 price crashes. For the version presented in this work, the constant chosen is 10 trading days. Larger numbers all work, the only issue would be choosing a constant that is too small such that brief periods of backwardation trigger a trade and then contango comes back to close out the position without any sustained holding period or purpose. The constant is even on both sides of the algorithm to enforce this idea. Since the strategy takes leverage in the short positions as a function of the number of periods presently in backwardation, the constant, as long as it is sufficiently large, does not matter. In fact, a large constant is actually more profitable because the algorithm consistently loses money in the earlier trading days.

The function to leverage the short position over the period of sustained backwardation is customizable. A starting point for experimentation is a simple linear function of the

[2] CL1CL9 is the price of the 9-month CL future minus the price of the 1-month CL future, which is the dollar value of contango or backwardation between the 8-month time difference.

number of periods presently in backwardation. This would mean on the first day of trading, if the algorithm shorts one futures contract, if it reaches the 100th day of trading, it would be short 100 futures contracts. This works well from a profitability perspective but given these sustained periods can be over 200 trading days, shorting a multiple of 200 the initial short is unreasonable for most leverage constraints. So the function chosen for the leverage factor is modified to be the square root of the number of periods of backwardation to cap leverage. The square root limits leverage yet allows for the latter trading days to be weighted more than the earlier days. For example, using square root, the 100th trading day has 10 times the initial leverage and the 225th trading day has 15 times the initial leverage, a difference of 5 compared to 125.

Lastly, what to purchase that gains from a fall in crude oil price. There are a few motivations behind including a second product in the trading strategy. Since the algorithm concentrates leverage at the end of its trading days and thus the largest profit and loss swings should be generated towards the end, longing a product that benefits from the fall in crude oil prices throughout the duration of the trade should help diversify the source of profitability in the event of the crash. There are a number of candidates to choose from that all trade relative to the price of crude oil to varying degree.

Outside of endogenous factors in the crude market motivating prices through supply and demand, inflation expectations, present dollar strength, and GDP growth expectations are amongst the top three candidates to impact or be impacted by crude oil prices (Alquist and Killian 2010). Inflation levels have been relatively stable and suppressed in volatility compared to the volatility of crude oil price in this time frame. Expectations of GDP growth are argued to motivate crude oil price, but again, GDP movement is sluggish compared to volatility in crude over the past decade. Also, it is difficult to find a tradable financial instrument to accurately track daily GDP growth expectations only months into the future. Combined with the fact that the furthest time spread examined is 9 months (CL1CL9), where not much growth can be gained or lost, expectations of inflation and GDP changes are not considered in the trading algorithm and the only product outside crude futures considered is the strength of the U.S. dollar.

The reasoning is since crude light futures are dollar denominated assets, there might be some degree of causality between the dollar and crude futures on various time frames. Consider a scenario where crude oil comes crashing down due to a major supply or demand related disruption. Now the USD can purchase more crude oil than moments before the crash, and since crude oil is such a large component of purchases made with the USD, the purchasing power of the USD might rise relative to its peers, the basket of major world currencies. Recall the opposite can occur as well, when OPEC considered raising first raising posted prices in 1973, the falling value of the USD was part of the motivation. Given the ease of tracking the USD with a variety of indexes and trading using ETFs, the dollar is used as the product traded outside crude oil.

The relationship between spot oil prices and the U.S. dollar has been explored extensively, with a 2012 paper modeling granger causality between spot oil prices and the strength of the U.S. dollar concluding that on longer than 3-month time frames, there is significant bi-directional causality between the U.S. dollar and spot oil prices but on a time frame of less than 3-months of lagged periods, the causality is only significant from crude oil price to U.S. dollar. In other words, this paper found that over longer time frames, it is difficult to pinpoint whether falling crude price leads to increased dollar strength or vice versa, but in a less than 3-month time frame, falling crude oil prices should lead to increased dollar strength or rising crude oil prices should lead to decreased dollar strength (Benhmad 2012).

This paper uses a dataset between 1970 and 2010, with spot prices and the U.S. dollar and an advanced wavelet based approach to model causality non-linearly. Since this trading strategy is based on daily data between 2007 and 2017, using CL1 (near month future) as a proxy for spot prices, verifying this result with a bi-directional autoregressive model and confirming the causality holds linearly is necessary before choosing the U.S. dollar as the product in the algorithm.

Given these considerations, the pseudocode is written more precisely:

```
For each trading day examined (
Constant = 10
If CL1CL9 > 0:
      Ctally+=1
If CL1CL9 < 0:
      Ctally=0
      Btally+=1
If Btally >= constant:
      Short CL9 * SQRT(Btally)
      Buy USD
If Ctally >= constant:
      Stop shorting CL9
      Sell all USD
)

Notes:
Reset all parameters after the algorithm completes a trade cycle
```

4.0 - The Data

Crude Oil: Quandl CHRIS Crude Light (CL) daily trading day futures opening price between 01/02/2007 and 03/01/2017. This data is the nominal price of CME CL futures on the given day with roll on the first of the month. Prices for CL1 and CL9 are used, which represent the 1 and 9-month futures, respectively. Since each data point is a trading day minus holidays, there are 2,567 data points across the time frame. So for example on 01/01/08, CL1 would expire one month after on 02/01/08 and CL9 would expire 9-months after on 10/01/08.

USD: DTWEXM is US Dollar Trade Weighted Index on given day provided by FRED St. Louis Fed, also 2,567 data points. DTWEXM is a weighted average of the foreign exchange value of the U.S. dollar against a subset of index countries outside the U.S. These currencies originate from the Euro Area, Canada, Japan, U.K., Switzerland, Australia, and Sweden. Note that on 15 points in the dataset, the value of DTWEXM was blank on a given day of crude trading. In such a case, the value from the previous date was pulled into the blank cell. This should not affect results as monthly smoothed averages are used to define relationships between crude and the dollar so 15 double values spread between 2,567 data points are negligible.

UUP is the PowerShares Deutsche Bank Dollar Index Bullish Fund provided by Nasdaq which tracks the value of the USD relative to the basket of six major world currencies - the euro, Japanese yen, British pound, Canadian dollar, Swedish krona, and Swiss franc. UUP is used in the trading model since UUP is a tradeable product and DTWEXM is an index. Though DTWEXM includes more countries in its weighted average, UUP provides exposure to the strength of the U.S. dollar suitable for the trading algorithm. UUP has a value for every day of CL and DTWEXM trading.

4.1 - The USD and Crude

A bi-directional lagged autoregressive model is constructed to test whether a given time series affects another using a granger causality test. CL1 and DTWEXM are both smoothed to monthly average values by summing all values in a given month and dividing by the trading days in the month and then further smoothed using a 3 month moving average. This allows exploration of lagged periods spanning monthly timespans. Percent change between each month satisfies the time series stationarity constraint and is assigned to the variables CL1P and DTWEXMP, plotted in the appendix.

CL1P is said to Granger cause DTWEXMP if the prediction of CL1P using its own lagged values and the lagged values of DTWEXMP is more accurate than the prediction of CL1P using only its own lagged values. To state this precisely, the equations[3] below are constructed

$$1\quad DT_t = a_0 + a_1 DT_{t-1} + a_2 DT_{t-2} + e_t$$

$$2\quad DT_t = a_0 + a_1 DT_{t-1} + a_2 DT_{t-2} + b_1 CL_{t-1} + b_2 CL_{t-2} + e_t$$

$$3\quad CL_t = a_0 + a_1 CL_{t-1} + a_2 CL_{t-2} + e_t$$

$$4\quad CL_t = a_0 + a_1 CL_{t-1} + a_2 CL_{t-2} + b_1 DT_{t-1} + b_2 DT_{t-2} + e_t$$

$$5\quad DT_t = a_0 + a_1 DT_{t-1} + a_2 DT_{t-2} + a_3 DT_{t-3} + a_4 DT_{t-4} + a_5 DT_{t-5} + a_6 DT_{t-6} + e_t$$

$$6\quad \begin{aligned} DT_t = {} & a_0 + a_1 DT_{t-1} + a_2 DT_{t-2} + a_3 DT_{t-3} + a_4 DT_{t-4} + a_5 DT_{t-5} + a_6 DT_{t-6} \\ & + b_1 CL_{t-1} + b_2 CL_{t-2} + b_3 CL_{t-3} + b_4 CL_{t-4} + b_5 CL_{t-5} + b_6 CL_{t-6} + e_t \end{aligned}$$

$$7\quad CL_t = a_0 + a_1 CL_{t-1} + a_2 CL_{t-2} + a_3 CL_{t-3} + a_4 CL_{t-4} + a_5 CL_{t-5} + a_6 CL_{t-6} + e_t$$

$$8\quad \begin{aligned} CL_t = {} & a_0 + a_1 CL_{t-1} + a_2 CL_{t-2} + a_3 CL_{t-3} + a_4 CL_{t-4} + a_5 CL_{t-5} + a_6 CL_{t-6} \\ & + b_1 DT_{t-1} + b_2 DT_{t-2} + b_3 DT_{t-3} + b_4 DT_{t-4} + b_5 DT_{t-5} + b_6 DT_{t-6} + e_t \end{aligned}$$

Equation 1 is the present value of DTWEXMP regressed on its own 1-month and 2-month lagged periods. Equation 2 includes the 1-month and 2-month lags of CL1P. The null hypothesis that CL1P does not Granger-cause DTWEXMP with two degrees of freedom is not rejected if and only if the lagged values of CL1P are jointly zero in Equation 2 according to a chi-squared test.

Equations 3 and 4 follow the same logic as above, this time considering whether the values on the lags of DTWEXMP are jointly significant on the present value of CL1P.

Equations 5 and 6 extend equations 1 and 2 from two degrees of freedom to six, meaning six months of lagged variables. Equations 7 and 8 do the same for equations 3 and 4.

[3] note DT denotes DTWEXMP and CL denotes CL1P

Granger Causality Results

Table 1: Granger Causality Results

Equation	Chi-Squared	DF	P > Chi-Squared
CL1P	3.98	2	0.137
DTWEXMP	10.08	2	0.006*
CL1P	12.91	6	0.045*
DTWEXMP	16.51	6	0.011*

Equation represents the dependent variable, so the first row

In the Granger causality test with two degrees of freedom the null hypothesis that the lags of DTWEXMP do not affect CL1P cannot be rejected at the 5% significance level (.137), however, the null hypothesis that lags of CL1 do not affect DTWEXMP is rejected (.006), thus, there is at least some degree of causality on DTWEXMP contributed by the lags of CL1P in the two month lagged model, agreeing with Benhmad 2012.

Increasing degrees of freedom by allowing for lagged variables up to 6 months, there is intra-causality between both dependent variable equations at the 5% significance level (.045 and .011) so there is no certainty that the lags of CL1 or DTWEXMP affect one-another in a singular direction, agreeing with Benhmad 2012.

This expands the result of the 2012 Benhmad paper with the key differences being using CL1 as a proxy for spot oil prices, a different tracking index for dollar strength, linear, non-wavelet based Granger causality, and on a monthly time-frame over a different decade of data.

The limitations of a Granger causality test include not proving true causality and not being able to capture non-linear effects. Given that the price of crude oil over the course of the trading algorithm should fall by the end, purchasing dollars over the course of the entire period only requires a linear effect to hold. In other words, as long as some degree of dollar strength is contributed to by purchasing power in crude oil, the relationship between the two during a price crash will be linear to some degree and thus tradeable. Regarding not proving true causality, that is a limitation worth accepting, as there is reason to believe a relationship should fundamentally exist.

This result verifies that the strength of the U.S. dollar should be an appropriate product to purchase given a suspected impending fall in oil prices on the 2-month level. Since sustained backwardation in the market anticipates falling oil prices continuously, it should follow that the value of the U.S. dollar should appreciate in value over the period the algorithm trades.

4.2 - Trading Algorithm Variables and Plot

CL1CL9 is the front month future price subtracted from the 9-month future price, on the present trading day. A positive number indicates contango in the market. A negative number indicates backwardation.

CL9F1T8 is the difference between the price of the 1-month future 8 months out from the present day minus the price of the 9-month future today. F1T8 refers to the price of the one-month future 8 months out from today. For example, on 1/2/2007 CL9 opened at $67 and CL1 on 8/1/2007 was trading at $77 so the value of CL9F1T8 associated with the date 1/2/2007 is $10. This value approximates the difference in expectation versus future realized value of the 9-month future on any given day. A positive number indicates that price rose more than expected. On the contrary, a negative number indicates that prices fell more than expected. This number is seen as the approximate gain or loss realized from shorting CL9 with only one unit today and holding until a buy to cover at expiry, ignoring some costs addressed later. The reason CL9F1T8 must be constructed to test this short futures model is because of the necessity to cover the futures short position before expiry. This construction assumes the position will be covered 8-months out from the day any given contract was shorted. In other words, the daily profit or loss in the futures position reflects how the position of futures positions taken on any given day will perform when covered 8-months out. Additionally, CL9F1T8 captures the premium collected from the decay of the costs of storage when short commodity futures.

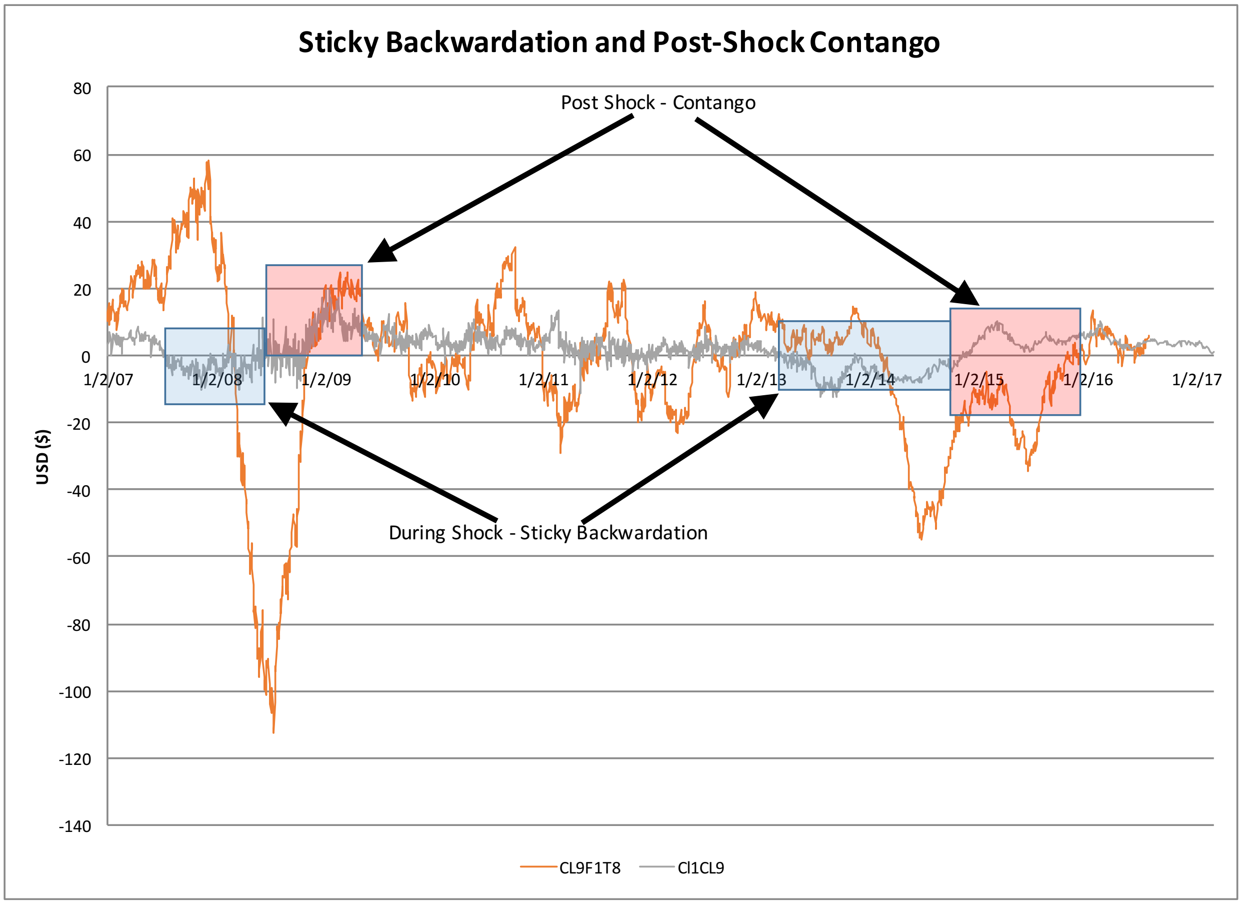

Figure 2: Sticky Backwardation

In the figure 2 above, the grey line (CL1CL9) can be viewed as the signal for the entry, exit, and leverage of the trade, the level of contango or backwardation present in the market. If CL1CL9 enters a period of 10 sustained days of backwardation, or negative value, the algorithm starts shorting futures as a function of the number of periods presently in backwardation while purchasing U.S. dollars. When CL1CL9 shifts from sustained negative to 10 days of positive value, the market is back in contango and the algorithm stops trading. The algorithm should trade in the blue zones and exit at the start of the red zones. As a sanity check, both of these zones satisfy as shocked prices. The orange value, CL9F1T8, corresponds to the approximated profit or loss realized from shorting the 9-month future on a given trading day. A $5 cost is built-in to the back test per futures contract to account for any miscellaneous fees, such as brokerage costs and partial fills. This fee is likely overstated, as a broker that charges $5 commission per futures contract is relatively expensive and partial fills should move towards the next best bid, where a gap of $5 is generous. The fees associated with the UUP ETF are negligible.

The periods of backwardation corresponding to 2008 and 2014 are referred to as BP1 and BP2, respectively.

4.3 - The Back Test

To test the trading algorithm, the profit generated is divided on a daily basis between UUP and CL. The initial short of the CL9 contract is one unit and the UUP daily profit is per one share. In reality, there is a minimum amount of crude futures required to trade in one transaction, the size of the contract is a multiple of barrels. For simplicity, that size is viewed as one barre. Since allocation between UUP and CL9 is not within the scope, the split plots assist in drawing conclusions suggesting possible allocation considerations. Note that source code is found in appendix. Cumulative profit plots are constructed by cumulatively summing across the columns in the daily profit arrays.

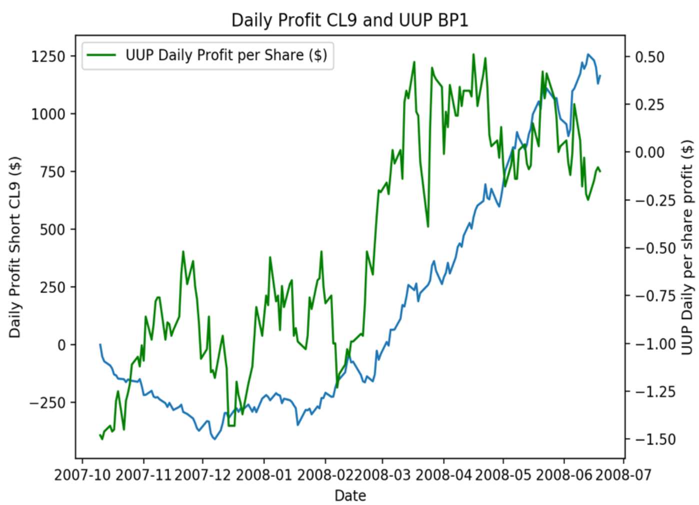

Figure 3: Daily Profit CL9 and UUP BP1

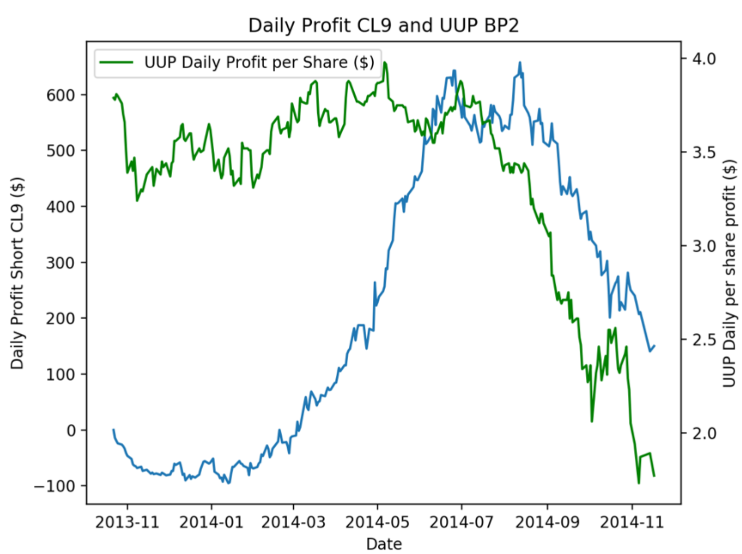

Figure 4: Daily Profit CL9 and UUP BP2

In Figure 3 and Figure 4 above, the daily profit per product per trading day is plotted for both BP1 and BP2. The green line represents UUP daily profit, corresponding to the axis on the right axis of the chart while the blue line represents CL9 daily profit, corresponding to the left axis. These lines are interpreted as how much money per barrel of CL9 or per share of UUP is gained or lost on a given day of trading. Negative values indicate losses.

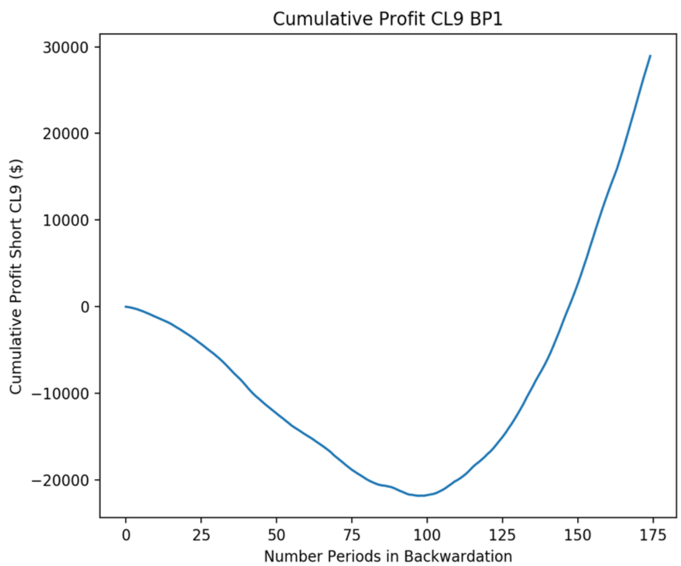

Figure 5: Cumulative Profit CL9 BP1

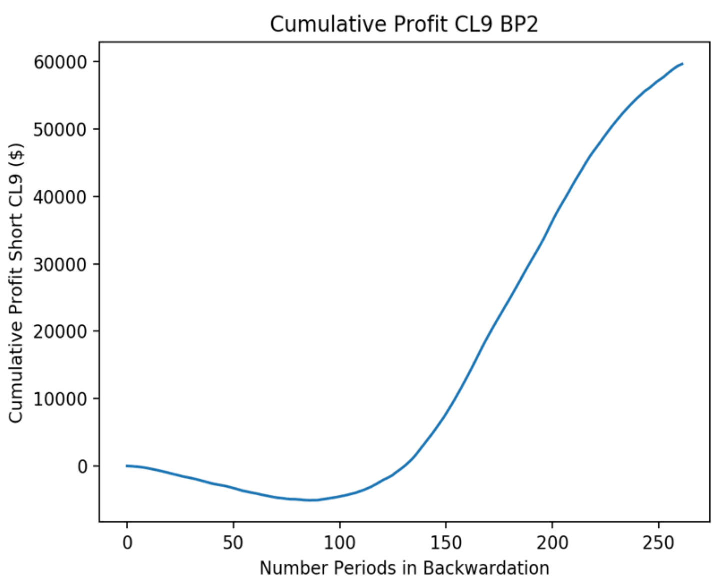

Figure 6: Cumulative Profit CL9 BP2

In figures 5 and 6, the cumulative profit for CL9 is plotted. This is the sum of the present day CL9 profit value and all the values from the previous days, representing how much profit CL9 has generated since the start of trading and the present day.

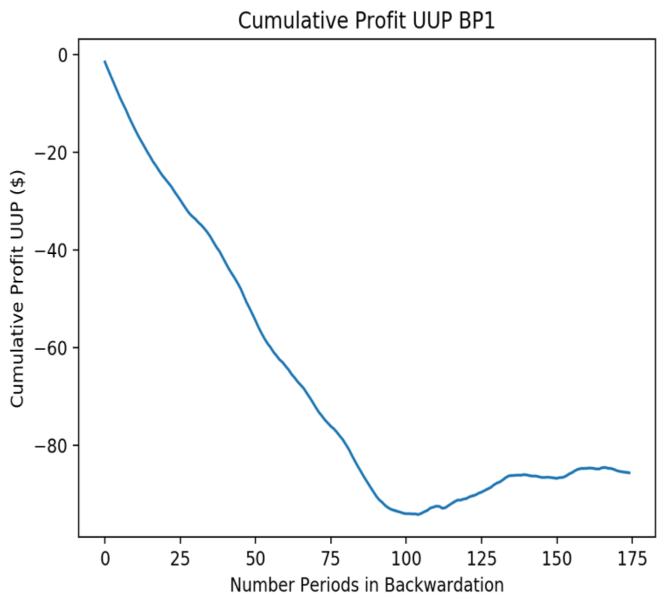

Figure 7: Cumulative Profit UUP BP1

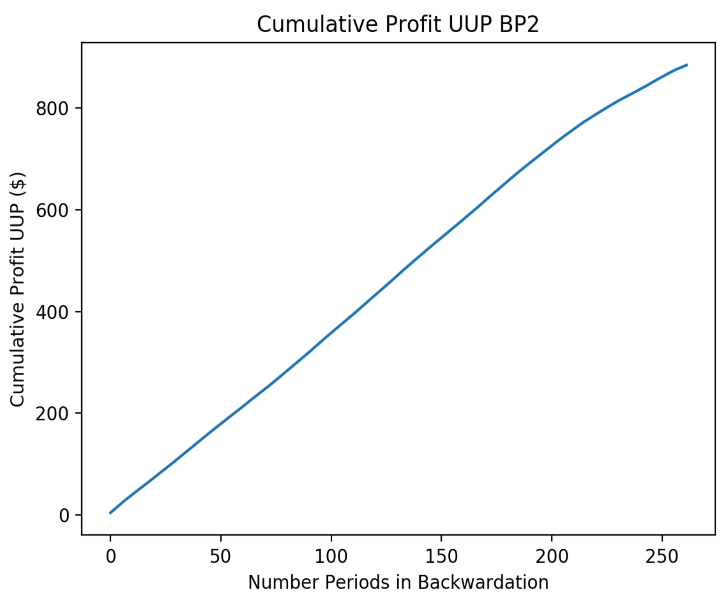

Figure 8: Cumulative Profit UUP BP2

In figures 7 and 8, the cumulative profit for UUP is plotted. This is the sum of the present day UUP profit value and all the values from the previous days, representing how much profit UUP has generated since the start of trading and the present day.

Performance Summary

Table 2: Performance Summary

Period	BP1	BP2
Cumulative Profit CL9	$28,929	$59,668
Net Required Capital CL9	$163,062	$261,051
Cumulative Profit UUP	-$86	$885
Net Required Capital UUP	$4,065	$5,702
Max Drawdown CL9	-$21,810	-$5,093
Max Drawdown UUP	-$94	$3.79
Max Leverage	13.23	16.18

The cumulative profit CL9 is the profit generated over the given period if the trader shorts a single barrel future unit of crude oil on the first day of the algorithm and adheres to the square root leverage formula, that strategy would have netted $28,929 in profit in BP1 and $59,668 in the price crash in BP2 per barrel. This profit represents a per barrel profit so shorting more barrels linearly increases profit, until a capital threshold is reached. The same applies for UUP as a per share profit.

Net required capital is the sum of the capital required to take all the short positions and dollar positions across all trading days. In other words, this is how much money you would need to do this with a singular per barrel contract or per share of UUP over the course of the entire trade. This capital can be entirely proprietary or leveraged on margin, affecting the return on proprietary investment accordingly.

Regarding percent return, since the strategy is not built with a specific portfolio allocation, as it is per barrel, and the leverage constraints do not dictate how much capital traded is proprietary versus borrowed from a broker, the percentage return is a function of how much risk, or margin, the trader is willing to take. For example, as a baseline for BP2, if the trader were to never borrow capital, the notional value of all the shorts initiated would cost around $261,000, netting the trader $59,668 on the $261,000. But if the trader were to borrow $100,000 for the leverage, the percentage return on proprietary capital will be higher. The above statistics are to show the strategy is profitable from a baseline one-barrel contract assumption, in reality, the trader would have to consider how much risk to take from brokerage margin to amplify return on capital. In BP1, due to the severe max drawdown, taking too much leverage would likely result in a margin call and failed trade. In BP2, this is less likely. The risk the trader is willing to take is a function of how much capital the trader provides versus borrows, left to the discretion of the trader, not the algorithm.

Max drawdown represents the maximum downside value of the given product during the trade period. In the cumulative profit charts, this represents the minimum value along the line. Max leverage is the final value in each period of the square root of the number of periods in backwardation.

The algorithm is profitable in both periods in CL9, with characteristically similar profit and loss curves that initially lose capital until the max drawdown and then recover on the crash. The max drawdown in BP1 represents about 2/3 of the eventual profits per barrel. In BP2, the drawdown is about 1/12 of the eventual profits.

In BP1, the UUP component of the strategy linearly loses money over the course of the trade. In BP2, the UUP component of the strategy profits linearly, resulting in the inverse slope plots of cumulative UUP profit between BP1 and BP2.

5.0 - Discussion and Extensions

The USD component of the strategy performed markedly differently in BP1 versus BP2. The former was a price crash as a result of a global credit bubble burst, a demand fueled downside, while the latter was a product of gross overproduction by Saudi Arabia as well as the United States. In the case of a global credit bubble, a multiple sigma event, causality between the U.S. dollar and crude oil is irrelevant, as both crude oil and the dollar crash. However, as seen in the second period of backwardation, if the crash in price results from overproduction, a supply side factor, the U.S. dollar performs well during the period of sustained backwardation.

While the backwardation in 2008 was initially likely a product of expectation that the refining bottleneck would subside followed by a sharp realized decline actually as a result of an exogenous factor, the backwardation in 2013 anticipated a supply side buildup and overproduction, endogenous factors to the crude oil market. If this strategy is implemented in the future, the speculator must ask why the backwardation is arising in the market. If there is expectation of some drop in future demand outlook as a result of exogenous factors to the crude oil market, such as a global credit bubble bursting, and naturally an expectation in drop of crude price as well as dollar strength, it makes sense to allocate most, if not all, capital into crude futures. On the contrary, if there is some expectation amongst producers that prices will fall as a result of a glut in supply or overproduction, the dollar trade becomes more likely and the allocation can reflect such confidence.

Given the trend towards overproduction, overcapacity, and glutting supply, with the last two years of depressed prices as primary evidence of such factors at play, I argue that if prices are shocked in the future, the factors motivating the price to come back down will likely be supply related as opposed to recession related. Predicting a recession is impossible, predicting that producers will flock to high prices and hedge out inventory with industry knowledge is probabilistic. Thus, if price were to be shocked in the future, it is more reasonable to assume it will come down behaving like it did in BP2 versus BP1.

Recall the fixed constant to define a sustained period of backwardation to enter is 10 days. Looking at all the plots above, increasing the constant for only the entry signal, the number of periods of backwardation required to be observed before entering the market, all the plots would be cutoff on the left. In other words, the algorithm would start trading later. For the cumulative profit CL9 curves in both periods, increasing the constant on entry would delay some of the earlier losses taken by the algorithm, increasing per barrel profit. For the cumulative profit UUP curves in both periods, increasing the constant on entry would mean less loss in BP1 and less profit in BP2. Thus, experimenting with an increased constant on entry when and if "sticky backwardation" arises is encouraged in the future.

Increasing the constant on exit would extend the plots further to the right, which is not displayed. Increasing of the constant on exit is greedy, as it forces the algorithm to trade longer when the market is no longer in backwardation. The exit should not be greedy so the constant of 10 trading days for contango is encouraged to be fixed in the future. The challenge with reducing the contango (exit) constant is if the market is in backwardation for 100 days and then slips into contango for 3 days and then back to backwardation for another 100 days, if the exit constant chosen was 2 days, the algorithm would have prematurely exited and re-entered. In other extensions, one can choose the exit constant depending on the number of days the market has been in backwardation, say 5%. At that rate, 200 days of backwardation would result in 10 days of contango required to exit. Regardless of the value of the constant, the trader should ask themselves why the contango is back in the market, similar to asking why the backwardation entered the market in the first place. If the answer to that question is because producers are done selling far month futures and are finished with their hedges, allowing the contango to shift back to the normal costs of storage, the trader should exit the position.

The major limitation of this algorithm is it requires the specific phenomenon of "sticky backwardation" in the market to enter the trade. If one wanted to implement this strategy right after the crash in 2014, they would still be waiting in 2017, as prices have yet to be shocked again and sustained backwardation is not present. Waiting can continue for years into the foreseeable future, as the events that promote shocked prices are abnormal and predicting when these events must occur is a guessing game. In fact, employing the view that negative supply shocks are actually a deflationary force on the long term price of crude oil as a result of the investment response to price outlined by Friedman for the internet and Parrilla for the crude market, the likelihood that such an algorithm can be implemented in the future should decrease as a function of the number of past shocks. In other words, since every successive price shock makes future price shocks less likely and given the proximity of the two shocks in the past decade and the shift towards renewable, non-crude energy and transportation, it is reasonable to assume the next price shock can be years, perhaps even decades, into the future.

There are other factors promoting U.S. dollar strength in the second time period as well, especially when considering “strength” as a function of relative value against a basket of other currencies. These other currencies could have been facing their own problems, such as stagnant growth and interest rates in Europe driving Euro weakness. When considering longing dollars against other currency pairs, the relative strength of the basket should be considered.

5.1 - Conclusion

The crude oil futures market was created after the first two price shocks to allow producers and importers to hedge expectations of supply and demand out in time. After studying the drivers behind the price changes during and after the shocks, it is concluded that the factors that motivate price to be shocked are unpredictable but prices should predictably fall from shocked levels. The futures curve can indicate when prices are likely to fall as a result of physical traders placing orders hedging against industry knowledge. A shift in the slope of the futures curve to sustained periods of backwardation, sticky backwardation, during shocked levels defines the entrance. A shift in the slope of the futures curve back to sustained contango, which is the normal pattern, defines the exit. The number of periods presently in sticky backwardation defines the leverage.

We verified that there is some degree of linear causality from crude oil prices to U.S. dollar strength in the short-term, so the strategy purchases U.S. dollars and sells crude oil futures when crude oil prices are likely to fall. In the second period of shocked prices, both components of this strategy are profitable, while in the first period of shocked prices, only the crude oil component of the strategy is profitable. This is a result of the global financial crisis and looking forward, it is hypothesized that if another price shock is to occur, the factors that motivate price to come back down are more likely to be endogenous to the crude oil market, as in 1985 and 2014, as opposed to a crisis like 2008, implying this strategy can be useful in the future.

The key limitation of this strategy is it requires a specific, sustained market condition that only arises during shocked prices, meaning the next time this strategy can be implemented is unknown. Since it can be argued that negative supply shocks are a deflationary force on the longer term price of crude oil, every successive supply shock can decrease the likelihood of future shocks and dampen long term prices to depressed levels. Thus, it is possible that this algorithm will become less useful with every successful use and possibly never be used in the future if oil prices continue to remain depressed.

Acknowledgements

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Bibliography - Literature

Abramson, Bruce. "ARCO1: An application of belief networks to the oil market." *Proceedings of the Seventh conference on Uncertainty in Artificial Intelligence*. Morgan Kaufmann Publishers Inc., 1991.

Alquist, Ron, and Lutz Kilian. "What do we learn from the price of crude oil futures?." *Journal of Applied Econometrics* 25.4 (2010): 539-573.

Baumeister, Christiane, and Gert Peersman. "The role of time-varying price elasticities in accounting for volatility changes in the crude oil market." *Journal of Applied Econometrics* 28.7 (2013): 1087-1109.

Benhmad, François. "Modeling nonlinear Granger causality between the oil price and US dollar: A wavelet based approach." *Economic Modelling* 29.4 (2012): 1505-1514.

Blackwill, Robert D., and Meghan L. O'Sullivan. "America's Energy Edge: The Geopolitical Consequences of the Shale Revolution." *Foreign Aff.* 93 (2014): 102.

Büyükşahin, Bahattin, and Jeffrey H. Harris. "Do speculators drive crude oil futures prices?." *The Energy Journal* (2011): 167-202.

Considine, Timothy J., and Donald F. Larson. "Uncertainty and the convenience yield in crude oil price backwardations." *Energy Economics* 23.5 (2001): 533-548.

Gately, Dermot, M. A. Adelman, and James M. Griffin. "Lessons from the 1986 oil price collapse." Brookings Papers on Economic Activity 1986.2 (1986): 237-284.

Gülen, S. Gürcan. "Efficiency in the crude oil futures market." *Journal of Energy Finance & Development* 3.1 (1998): 13-21.

Kilian, Lutz, and Daniel P. Murphy. "The role of inventories and speculative trading in the global market for crude oil." *Journal of Applied Econometrics* 29.3 (2014): 454-478.

Lacalle, Daniel, and Diego Parrilla. "The Energy World is Flat: Opportunities from the End of Peak Oil." (2015).

Morse, Edward L. "Welcome to the revolution: Why shale is the next shale." *Foreign Aff.* 93 (2014): 3.

Silvapulle, Param, and Imad A. Moosa. "The relationship between spot and futures prices: evidence from the crude oil market." *Journal of Futures Markets* 19.2 (1999): 175-193.

Yergin, Daniel. "The prize: The epic quest for oil, money & power." (2011).

Bibliography - Data

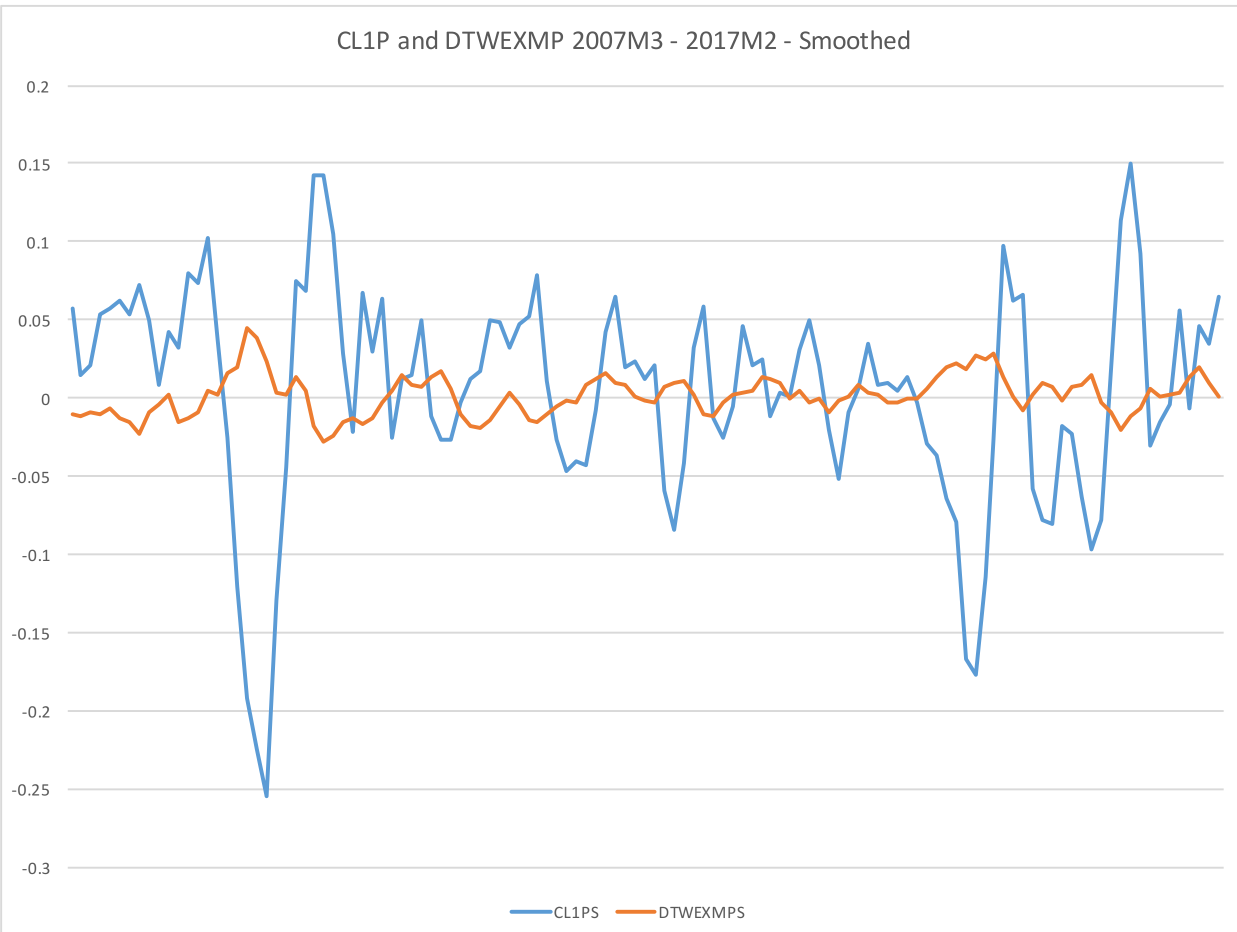
UUP ETF: http://www.nasdaq.com/symbol/uup/historical

CME CL Futures: https://www.quandl.com/data/CHRIS/CME_CL9-Crude-Oil-Futures-Continuous-Contract-9-CL9

https://www.quandl.com/data/CHRIS/CME_CL1-Crude-Oil-Futures-Continuous-Contract-1-CL1-Front-Month

DTWEXM: Board of Governors of the Federal Reserve System (US), Trade Weighted U.S. Dollar Index: Major Currencies [DTWEXM], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DTWEXM

Appendix



Appendix 1: Smoothed CL1P and DTWEXMP used for Granger Causality Test

Source Code

```
import numpy as np
import matplotlib.pyplot as plt
import csv
import pandas as pd
import math

def load_data(csvname):
    # load in data
    reader = csv.reader(open(csvname, "rb"), delimiter=",")
    d = list(reader)

    data = np.array(d)

    real_diff = np.array(data[:,0]).astype("float")
    contango = np.array(data[:,1]).astype("float")
    date = np.array(data[:,2]).astype("string")
    uup = np.array(data[:,3]).astype("float")

    return date, contango, real_diff, uup

def gen_backwards_time(d,c,rd, uup):

     backwardation_08 = []
     backwardation_15 = []

     count = -1
     length = 0
     flag = 0
     tango_sus = 0
     for cl1cl9_over_cl1 in c:
          count+=1
          if count == 1713: #to split into bp1 and bp2
               length=0
               tango_sus=0
               flag = 1
          if cl1cl9_over_cl1 < 0:
               length+=1
               if (length >= 10 and flag == 0):

     backwardation_08.append([d[count],c[count],rd[count],
uup[count]])
               if (length >= 10 and flag == 1):

     backwardation_15.append([d[count],c[count],rd[count],uup[c
ount]])
          if cl1cl9_over_cl1 >= 0:
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                tango_sus+=1
                if tango_sus >= 10:
                     length=0
                     tango_sus=0

     return backwardation_08, backwardation_15


def daily_simple_leveraged_short(N3arr):

     profit_arr = [] #date, profit or loss from shorting cl9 +
buying USD

     period = -1
     #print len(N3arr)
     for d_c_rd in N3arr:
          period+=1
          #profit_arr.append([d_c_rd[0][period],-
1*period(d_c_rd[2][period])])

     profit_arr.append([N3arr[period][0],(N3arr[period][2]+5)*-
1*math.sqrt(period),(25.14 - N3arr[period][3])])
          #25.14 for bp2, 22.74 for bp1, final value of USD on
closing day


     return profit_arr

def cumuluative_profit_arr(arr):

     cum_p_arr = []
     prof_cl1 = []
     for p_ele in arr:
          prof_cl1.append(p_ele[1])

     period = 0
     summ = 0
     for dp in prof_cl1:
          summ+=dp
          period+=1
          cum_p_arr.append(summ)

     plt.plot(cum_p_arr)
     plt.ylabel("Cumulative Profit Short CL9 ($)")
     plt.xlabel("Number Periods in Backwardation")
     plt.title("Cumulative Profit CL9 BP2")

     return cum_p_arr
```

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def cumuluative_profit_arr_usd(arr):

     cum_p_arr = []
     prof_cl1 = []
     for p_ele in arr:
          prof_cl1.append(p_ele[2])

     period = 0
     summ = 0
     for dp in prof_cl1:
          summ+=dp
          period+=1
          cum_p_arr.append(summ)

     plt.plot(cum_p_arr)
     plt.ylabel("Cumulative Profit UUP ($)")
     plt.xlabel("Number Periods in Backwardation")
     plt.title('Cumulative Profit UUP BP2')

     return cum_p_arr

def plot_profits(arr2d):

     x,y,z = zip(*arr2d)
     x = [pd.to_datetime(d) for d in x]
     fig, ax1 = plt.subplots()
     ax2 = ax1.twinx()

     lp1 = ax1.plot(x,y,label="Daily Profit Short CL9 ($)")
     ax1.set_xlabel('Date')
     ax1.set_ylabel('Daily Profit Short CL9 ($)')
     lp2 = ax2.plot(x,z, color='g', label="UUP Daily Profit per
Share ($)")
     ax2.set_ylabel('UUP Daily per share profit ($)')

     plt.legend()
     plt.title('Daily Profit CL9 and UUP BP2')
     plt.show()

d,c,rd, uup = load_data("stickyb.csv")
bp1,bp2 = gen_backwards_time(d,c,rd,uup)

simplexprofit = daily_simple_leveraged_short(bp2) #plot bp1 or
bp2 here

prof_cl1 = []
prof_usd = []
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for ele in simplexprofit:
     prof_cl1.append(ele[1])
     prof_usd.append(ele[2])

def writeappendix(arr):
     with open('bp2clcum.csv', 'wb') as f:
          writer = csv.writer(f)
          writer.writerows(arr)

writeappendix(simplexprofit)
# Summary Stats
print "Cumulative Profit CL9: " + str(np.sum(prof_cl1))
print "Cumulative Profit UUP: " + str(np.sum(prof_usd))

cumcl1 = cumuluative_profit_arr(simplexprofit)
cumuup = cumuluative_profit_arr_usd(simplexprofit)

print "Max Drawdown CL9: " + str(np.amin(cumcl1))
print "Max Drawdown UUP: " + str(np.amin(cumuup))

print "Leverage Factor: " + str(math.sqrt(len(simplexprofit)))

#Cumulative Plots
cumuluative_profit_arr(simplexprofit)
cumuluative_profit_arr_usd(simplexprofit)

#Daily Plot
plot_profits(simplexprofit)
```