Corn, Oil, and Drought: A Time-Varying Parameter Analysis

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The U.S. corn market responds in powerful ways to shifts in crude oil prices and potential droughts, yet not in consistent patterns. In this research, we use a time-varying parameter regression methodology to highlight how the corn market's reaction to oil and drought has changed over time, and more specifically to highlight the characteristics of corn, oil, and drought price interaction that seem to be more significant than just tracking typical price momentum and volatility metrics and assuming persistent and consistent patterns.

In this preliminary case study of dynamic pattern shifts for corn, oil, and drought, we first introduce our time-varying parameter regression methodology by comparing it to traditional regression methods. Our intention is to emphasize the need to use statistical methods that are dynamic in nature, adapting to critical pattern changes over time. Second, we provide a description of our data set. We are not trying to create a complete or definitive model of corn pricing, and as such certain factors that may be associated with corn pricing, such as inventories or ethanol regulations, have been omitted to keep the focus on time-varying statistical methods and the importance of identifying pattern shifts as straightforward as possible. With data and our time-varying parameter methods guiding us, we then turn to a narrative of how the corn market has reacted to oil price shifts and droughts over time. Our key takeaway is that patterns in the corn market that are often considered to be stable are nothing of the sort. A dynamic pattern analysis reveals interesting characteristics of when oil price changes and drought potential are more likely to have a price impact on corn than not. Future research may expand the number of factors related to corn pricing to provide a more complete model.

In the case of oil, our findings indicate that oil prices had little influence on corn prices through the 1980s and 1990s, despite ethanol subsidies being introduced during the OPEC crisis of the 1970s. Oil prices did not become a consistent influence on corn prices until the U.S. shale revolution led initially to much lower oil prices in the U.S. than globally. Once the U.S. export infrastructure developed to support the new shale production, U.S. oil effectively reconnected to global markets, and interestingly, oil lost its influence on corn prices until upward oil price surges ahead of and during the initial phases of the Russian invasion of Ukraine returned oil to an important influence.

Our dynamic analysis of the impact of droughts on corn prices shows a quite dramatic change occurring with the 2012 severe drought. Prior to the 2012 drought, corn prices were only decidedly impacted by a drought when one actually occurred, essentially following a cyclical influence pattern. Even a little before

2012, but especially afterward, our drought indicator achieved a much more persistent and consistent influence on corn prices, whether or not a crop-reducing drought actually occurred. The observed tendency in our research of corn prices suggests a change in the pattern of how drought indicators appear to have influenced corn prices.

Statistical Methodology

A time-varying parameter (TVP) regression method presents a more nuanced approach to modelling commodities markets compared to standard regression techniques, especially where the evolution of estimated coefficients is important. The model dynamically adjusts to changes in market conditions by allowing estimated coefficient flexibility across time, providing the ability to research the changing relationship of variables. TVP models weigh the importance of data points based on recency. With TVP, the most recent observations have the greatest weight, while older observations fade, but are never entirely forgotten. Our contention is that market participants behave this way, in that they give more weight to the most recent news and over time the impact of old news fades away.

Comparing TVP analysis with other types of regression paints a more concrete picture of using a time-decay methodology. A traditional regression model treats every data point with equal weight attempting to capture the relationship over time with a constant estimated factor coefficient. A rolling window regression, in contrast, fits many smaller lines based on smaller chunks, or windows, of data, effectively repeating a traditional regression many times on smaller datasets. Unlike TVP, rolling window regressions do not consider any data outside the specific window for each window model, and every datapoint inside each window is weighted equally, regardless of recency. Finally, an expanding windows regression fits a new line of best fit, and thus calculates a new coefficient, for every new data point. Still, every data point gets the same weight, and the result over the full time period converges on the standard, full window, regression.

In Figures 1 and 2, each of these plots shows the estimated beta coefficient for oil, or the week-to-week percent change in the price of corn associated with the week-to-week percentage change in the price of oil. The observed estimated coefficient relating oil to corn appears stable and consistent with these traditional regression methods where each data point receives equal weight. As we will observe later, TVP produces a strikingly different picture.

TVP analysis weighs observations based on time. In our TVP approach we introduce a time-decay parameter, which we call lambda. Setting our time-decay parameter equal to one reproduces a traditional expanding window regression analysis, as all data points are given an equal weight. Using a time-decay parameter of less than one introduces exponential weighting which gives more recent observations more weight and each preceding observation less weight. For intuitive purposes, our time-decay parameter, lambda, is chosen in relation to the desired half-life of the model. For example, a one-year half-life means that 50% of the influence comes from data more recent than one year, and the other 50% comes from data that is older than one year. When half-life falls, the model forgets data faster, which increases the volatility of the estimated factor coefficient yet may pick-up a shift in factor influence a little quicker. The choice of half-life is both an art and a science and depends on the level of granularity desired in the model.

Figure 1
Corn ~ Oil (Sample Regular Regression)

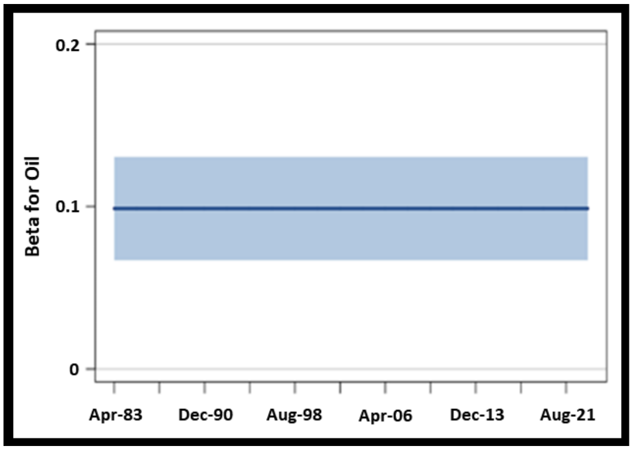
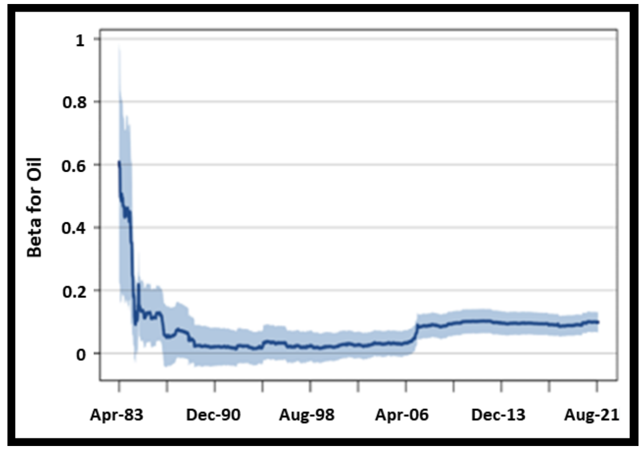


Figure 2
Corn ~ Oil (Sample Expanding Window)



Data

The data on oil and corn commodity prices in our model came from the Bloomberg Professional Terminal, using the most active futures contracts for corn and for West Texas Intermediate (WTI) crude oil. All of our data is weekly. Our corn and oil raw data commence in April 1983, driven by the start of crude oil futures trading on the New York Mercantile Exchange (NYMEX), and runs through June 2023. For each TVP model used in this research we provide the specific data periods used when that model is discussed.

For drought severity, raw data was taken from the U.S. Drought Monitor, a dataset produced through collaboration between the National Drought Mitigation Center, the U.S. Department of Agriculture (USDA), and the National Oceanic and Atmospheric Administration (NOAA). Drought severity data is weekly and commences in January 2002 through June 2023.

To come to a meaningful index of drought specifically for the U.S. corn belt, layers of filtering to account for severity of drought by state relative to corn production potential by state were deemed important. The Drought Monitor has established six categories of drought severity, from "None" (normal or wet conditions), then D0 to D4 (exceptional drought). Each of these categories is associated with a Standardized Precipitation Evapotranspiration Index (SPEI) range, a measurement that uses both precipitation and evapotranspiration events to determine drought severity. This range allowed us to quantitatively compare the six categories. See Figure 3. For each state within the U.S. corn belt, multiplying the relative state corn production potential by the absolute value of the SPEI and summing the weighted SPEI values created an aggregated drought index metric that could be compared across states in each time period. This means that our drought index as used in the TVP research shows a larger positive number when drought conditions are more severe.

Our standardized relative state corn production potential weighting is an arbitrary judgement. Both acreage intended to be planted, acreage actually planted, and production achieved at the end of the season can be influenced by farmers' perceptions of developing weather conditions as well as relative price assessments between alternative crops competing for scare agricultural land, such as soybeans and wheat. In this preliminary research, we wanted to keep the analysis as simple as possible, so we opted to apply the same state production potential weights for every weekly data observation. Severe droughts tend to spread across most states in the U.S. corn belt, but not necessarily evenly as drought conditions often start in more western states and spread eastward. We note, though, that our drought severity index qualitatively appears to correspond well to severe drought years. Figure 4 provides an illustrative example of how our drought severity index is created for each week in our data set.

Figure 3
Drought Index Architecture – Drought Severity Categories

Category	Description	Example Percentile Range for Most Indicators	Values for Standard Precipitation Index and Standardized Precipitation-Evapotranspiration Index
None	Normal or wet conditions	31 or above	-0.49 or above
D0	Abnormally Dry	21 to 30	-0.5 to -0.79
D1	Moderate Drought	11 to 20.99	-0.8 to -1.29
D2	Severe Drought	6 to 10.99	-1.3 to -1.59
D3	Extreme Drought	3 to 5.99	-1.6 to -1.99
D4	Exceptional Drought	0 to 2.99	-2.0 or less

Figure 4
Drought Index Architecture

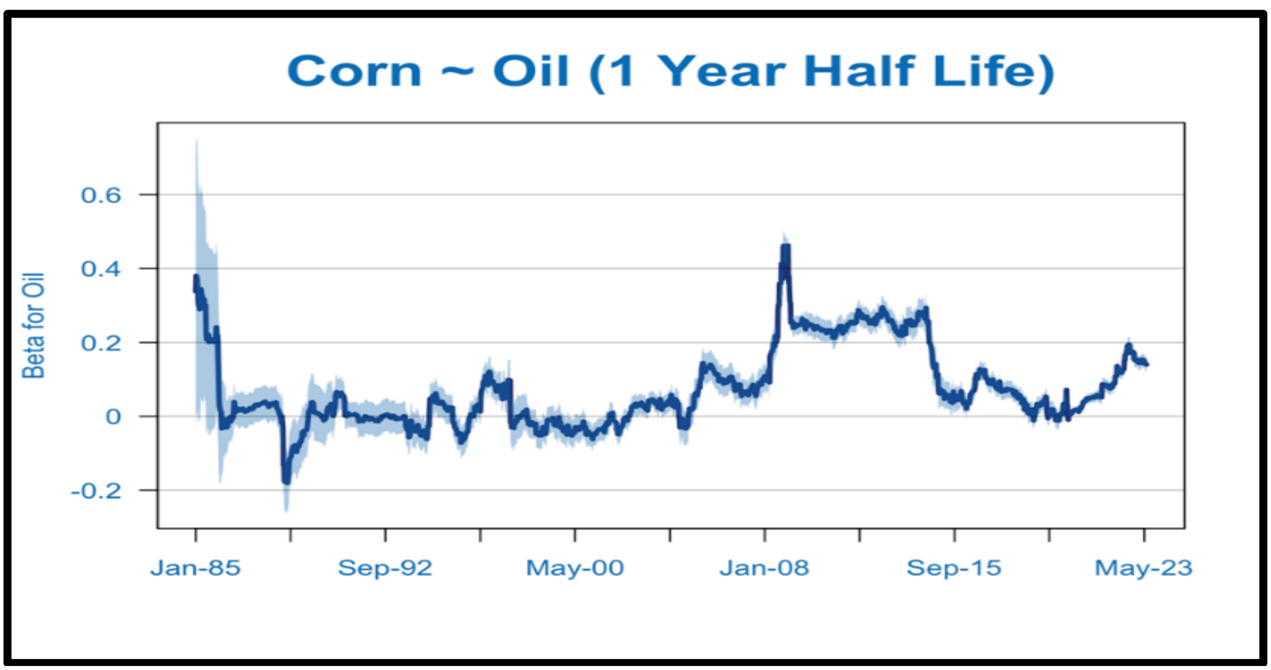
State in the Corn Belt (Note some states that produce corn are not typically included in the definition of the U.S. corn belt)	Representative Percent of Total Production Potential in the U.S. Corn Belt (Weight for the Drought Index)	Illustrative Drought Readings from the Drought Monitor (hypothetical)	Example of Drought Index Calculation (uses absolute value of drought reading by state, higher values indicate more severe drought)
Iowa	26.15%	-1.4	0.37
Illinois	24.06%	-1.1	0.26
Indiana	10.03%	-1.1	0.11
Kansas	6.17%	-1.7	0.10
Missouri	5.13%	-1.6	0.08
Nebraska	16.74%	-1.7	0.28
Ohio	6.07%	-0.9	0.05
Wisconsin	5.65%	-1.3	0.07
Total	**100.00%**		**1.34**

Dynamic Statistical Results

We created two TVP models to investigate the relationships between corn, oil, and drought. The first modeled the relationship between corn and oil using week-over-week percent changes in price with a 1-year half-life over the timeframe from January 1985 through June 2023. We want to combine our model results with historical context to discover patterns and build intuition about the changing relationships. Note that each plot does not display the price of corn or oil, but rather the estimated beta coefficient which measures the strength of the relationship between corn and oil, or how much change in the price of corn is associated with a one-unit change in the price of oil. We centered our historical contextualization around four points of particularly strong volatility in the model, as indicated below. While each event or shock is unique, we expect that considering the similarities in the effect on prices and effect on the model's beta will be insightful. Our interpretation refers to Figure 5.

In 1984, national corn production increased 83% from a drought diminished 1983 crop.[1] Known as the 1984 Corn Yield Rebound, the upswing flooded the market and depressed prices. In the mid-1980s, oil prices dropped sharply from the OPEC-induced relatively high prices from the 1970s and early 1980s. To achieve stabilization, OPEC decreased production from 1982 to 1985, but many OPEC states continued to produce above quota level. In 1986, as part of the minority implementing cuts, Saudi Arabia refused to continue to carry the mantle of oil market stabilization and ditched output control. As Saudi production more than doubled, the price of crude plummeted.[2] Our model reflects this shock, as the estimated beta coefficient plunged to close to zero, indicating that oil, at least for the time being, had lost its influence on corn prices.

Figure 5
Corn ~ Oil, 1 Year Half Life, January 1985 – June 2023



During 2007-2008, an opposite crisis provides a useful counterexample. Policies like export restrictions caused panic buying from importers and skewed price signals, driving global price increases. [3] Prices for staples like rice increased 224% and corn 89%, creating widespread food insecurity. These shocks coincided with a historic rise in the estimated beta for oil relative to corn prices.

In 2012, another yield shock arose, with corn and soybean yields the second best in history.[4] The yield shock happened to occur when U.S. crude oil prices were exceptionally low due to rapid production increases of shale oil. Like in the mid-1980s when oil prices declined, the negative oil price shock almost totally neutralized the estimated beta coefficient back to 0.

These examples provide two takeaways. The first is that the alignment of beta and historical shocks provides qualitative support of the ability of the TVP model to identify pattern shifts in the influence of key factors. This type of empirical analysis is not possible with standard regression techniques that weight all data points equally over the time period being analyzed.

The second takeaway involves how the relationship between corn and oil may dramatically change given a shift to a new oil price regime. While we have many data points included in the study, a closer examination of the historical context suggests that there are only two oil regime shifts episodes to consider, so be especially cautious concerning our interpretation. What we can observe is that on the occasions when oil prices surge upward, the relationship between corn and oil becomes stronger and more positive. Conversely, when oil prices fall sharply and enter a new regime of more persistently lower oil prices, the corn-oil relationship becomes very weak or almost non-existent as evidenced by a near-zero estimated beta coefficient. That is, in a relatively low oil price regime, a change in the price of oil is associated with far less movement in the price of corn.

Expanding on our first model, we adjusted half-life from 1 to 2 years and focused the timeframe from January 2002 to April 2023. Figure 6 shows the estimated oil beta coefficient with the longer half-life for the time-decay parameter. Changing the half-life illuminated interesting pattern changes. First, the effect of the 2007-2008 Food Price Crisis remains prominent in the plot. However, the period 2012-2015 has changed. While the 1-year half-life model showed the most significant shock starting around 2012, the 2-year half-life model picks up the drop in beta later, around 2013. While 2013 certainly did see a large drop in the price of corn (of almost 10%), the difference between the two models shows the effects of changing the half-life.[5] The 1-year model is more volatile and responsive to new data because data is forgotten more quickly. Perhaps this is why the 1-year model began to show the effect of shocks on the beta earlier, the 2-year model simply needed more data for the effect to become large enough to move beta noticeably. Our point here is that the choice of the time-decay parameter matters when using TVP methods, and we suggest experimenting with different time-decay parameters can be important.

We also want to highlight the importance of studying the estimated intercept or constant term when using a TVP methodology. Figure 7 refers to the constant variable or intercept term with a 2-year half-life. The estimated intercept term attempts to capture the variance in the price of corn that the oil factor did not capture. From an intuitive perspective the intercept term may be considered a measure of our ignorance, or put another way, when the intercept term is statistical important it can indicate that additional factors should be included in the model. The period from 2008 through 2013 strongly suggests that more factors need to be considered when developing a more complete model of corn pricing.

Figure 6
Corn ~ Oil, 2 Year Half Life, January 2002 through June 2023

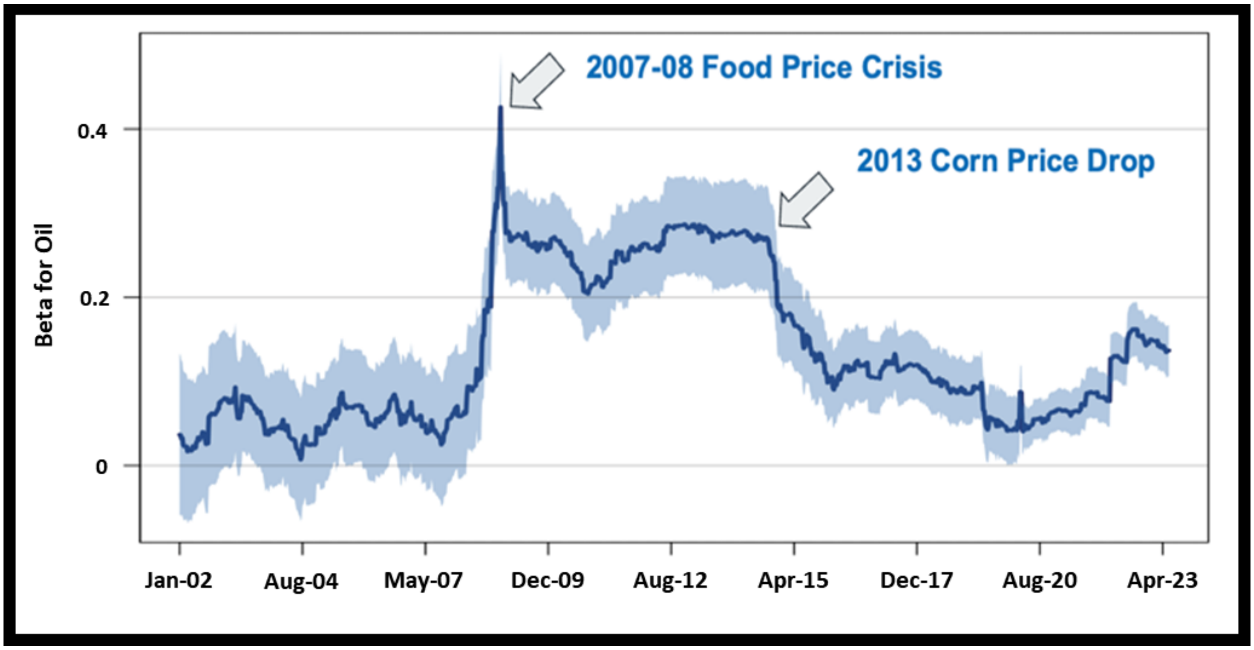
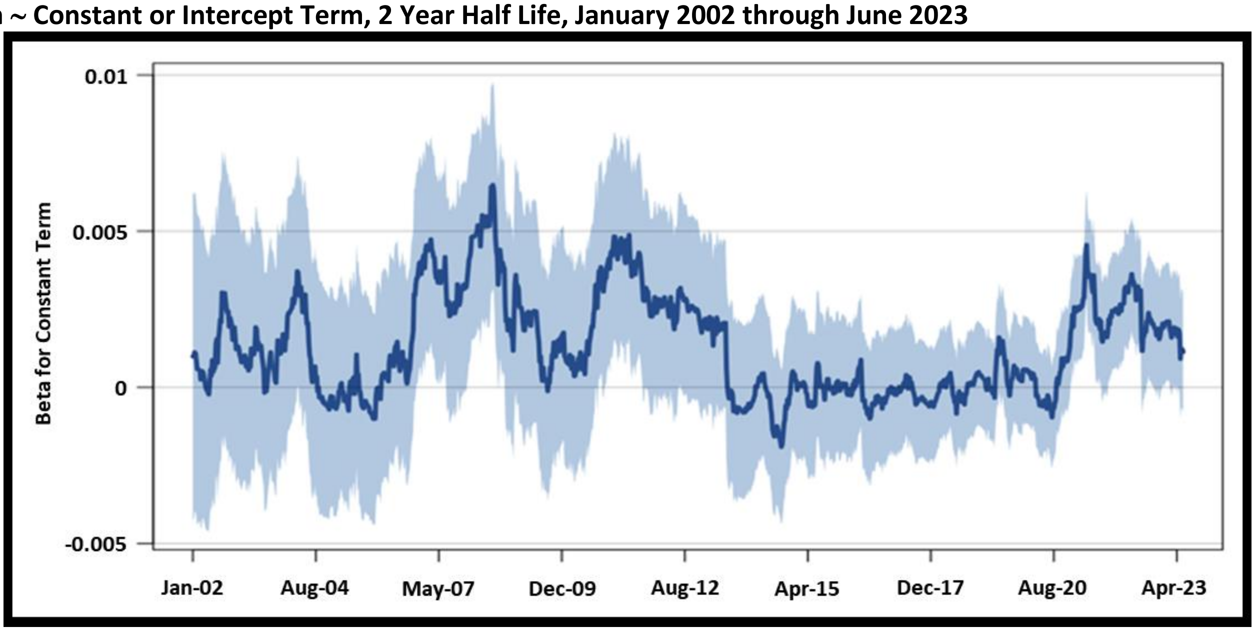


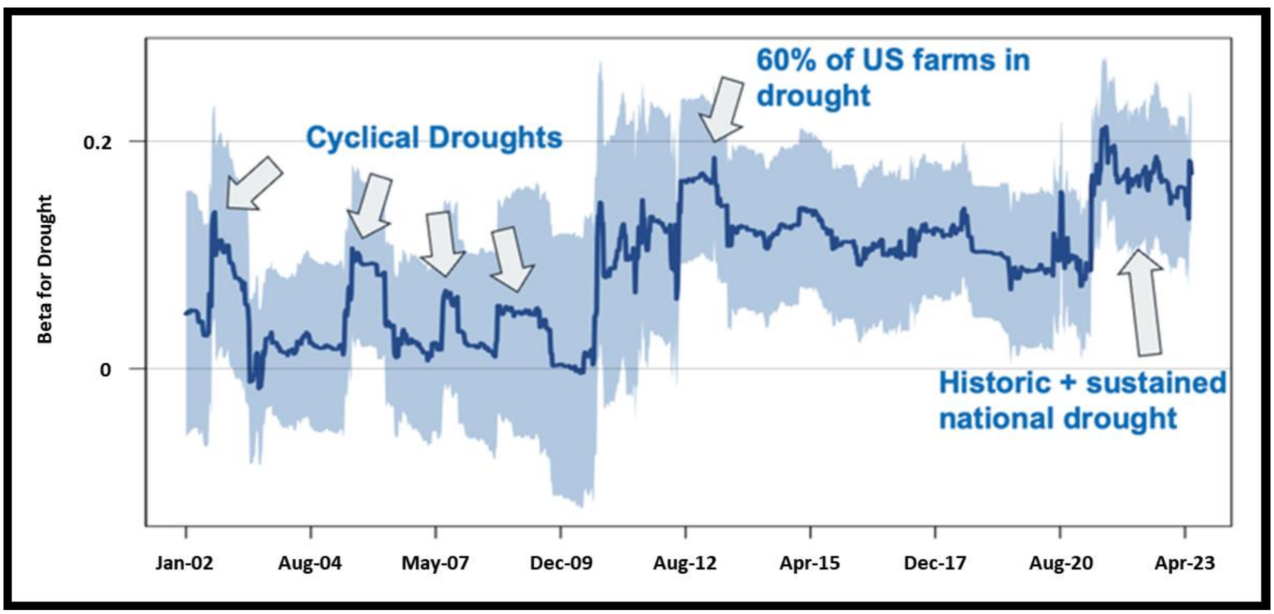
Figure 7
Corn ~ Constant or Intercept Term, 2 Year Half Life, January 2002 through June 2023



We now turn to our analysis of how drought severity may influence corn pricing. Our second model again investigated corn, but this time in relationship to our drought index variable and with a 2-year half-life.

Our TVP empirical model results, as shown in Figure 8, illustrates an interesting potential evolution in the relationship of droughts to corn pricing. From 2002-2009, drought shocks and their attendant estimated betas were roughly cyclical, with each drought creating similar shaped jumps and recoveries in data. Even though each of these four cases is of a slightly different length and intensity, the consistency is remarkable compared to after 2009. After 2009, two 2 events or episodes draw our attention. The first is the historic drought of 2012 in which 80% of agricultural land experienced drought.[6] This was associated with a record high plateau of the estimated drought beta only matched recently. The second is the historic and sustained national droughts the United States has been experiencing since 2020.[7] While slowly lessening in severity, August 2020 onward as seen an elevated beta unmatched in length and magnitude.

Figure 8
Corn ~ Drought Severity, 2 Year Half Life, January 2002 through June 2023



Taking a wider view, trends from 2002 paint a possible picture for the potential future movement of the relationship between drought and corn. The 95% confidence interval shading of the plot makes the clear upward trend related to drought severity as observed with the estimated beta coefficients. Three distinct periods, from 2002-2009, 2009-2020, and 2020-present each show a consistently higher beta than the one before. This suggests that as time goes on, there is the possibility that drought will have a greater and greater impact on corn prices. We offer an intuitive interpretation. As global climate change continues, the prevalence and severity of adverse weather events like drought will only worsen. Thus, the importance for businesses of hedging the rising risk and uncertainty from these weather events with financial instruments like weather futures and options may also continue to rise.

Future Research and Conclusions

We consider this research as a preliminary work to illustrate the value of using time-varying parameter methodology. Our focus has been on using two important factors, oil prices and drought severity, to highlight the importance of using dynamic statistical methods that can identify pattern shifts. We recognize that there are a multitude of ways the application of this model could be expanded using additional factors. A more complete study of the corn market would expand the list of possible influencing factors, such as inventories (Wright 2011) as well as the ramping up of export activity in Latin America, especially Brazil, as a repercussion of heightened US-China trade tensions. Our drought index could be expanded to encompass different regions of interest outside of the U.S. Corn Belt, such as competing production regions in Brazil. More exploration into the impact of biofuels following the research of Avalos and Lombardi (2015) might also yield additional insights.

What we observed, however, even in this limited study was that the relationship between variables like oil, corn, and drought are anything but steady. By using a time-varying parameter model, we succeeded in capturing the changes in these underlying relationships across a wide historical breadth, yielding valuable historical insights and intuitions and how these relationships change in response to varying conditions and shocks.

Endnotes

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