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Spread Trading in Corn Futures Market

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ABSTRACT

The non-linear relationship between old crop – new crop year spreads in corn futures market and stock-to-use (S-U) ratios published by the United States Department of Agriculture is analyzed. Using a non-linear logarithmic smooth transition regression (LSTR) model, we capture asymmetric market behaviors in high and low S-U regimes. Capturing this relationship and understanding the non-linear aspects of the relationship is of interest of grain merchandizers and speculators in the market. A spread trading strategy is simulated for the sample period, January 1985 through April 2015, to determine if the non-linear relationship is a profitable arbitrage opportunity in the market.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1 Problem

There is a limited, but growing literature that analyzes non-linear price relationships in commodities markets (e.g. Holt and Craig, 2006; Balagtas and Holt, 2009; and Ubilava, 2012). There are many reasons why commodity price behavior may be nonlinear. For example, regime changes brought about by government policy interventions, weather events, technology changes, transaction costs or restrictions on commodity arbitrage could result in differing price impacts in terms of size and duration, and as such, these price impacts may be better explained in a nonlinear versus a linear framework. To date, there is no previous research that has attempted to uncover potential nonlinearities between corn stock-to-use (S-U) ratios, which are reported monthly in United States Department of Agriculture's (USDA), World Agriculture Supply and Demand Estimate (WASDE) reports, and old crop – new crop corn future spreads. However, economic theory related to cost-of-carry and supply of storage would suggest that low S-U regimes should induce different futures spread behavior than high S-U regimes. Thus asymmetric nonlinear price dynamics are likely a prominent feature of corn futures spreads. A better understanding of corn futures spreads dynamics is of particular practical relevance to merchandisers and speculators who trade corn futures markets, as well as to providing a contribution to the supply of storage literature.

1.2 Objectives

There are two main objectives to this study. First, to determine if nonlinear price behavior in corn futures markets can be attributed to the relative level of corn S-U numbers using a logistical smooth transition regression (LSTR) modeling framework. Then second, to see if the LSTR model can provide a profitable corn futures spread trading strategy.

1.3 Approach

The approach for this study is to compare the in-sample model fit between a simple linear model and a nonlinear LSTR model. So first we specify and estimate a linear, ordinary least squares (OLS) model, which regresses old crop - new crop corn futures spreads on S-U ratios. Then we specify and estimate a non-linear, LSTR, to again model the effect of S-U ratios on old crop- new crop spreads. Further comparisons between the two models will be made by estimating their respective out-of-sample forecasting performance. Specifically, both the linear and non-linear models will be used to construct a trading strategy to determine if market participants can use OLS or LSTR models to generate a profitable strategy.

1.4 Outline of Study

Section 2 of this study will discuss background literature related to cost-of-carry and supply of storage theory, S-U ratios and when and how they are reported in WASDE reports, and futures spread relationships. In addition, the basic concepts underpinning the nonlinear LSTR model will be presented. Section 3 of this study will discuss the two different modeling approaches used for analysis; linear and non-linear approaches. Section 4 of this study will discuss the data; present models estimates; and analyze the empirical results. The final chapter, section 5 of this study will discuss all the results and contributions to relevant literature and will briefly discuss potential future studies.

2. BACKGROUND

2.1 Key Concepts

Being familiar with what a World Agriculture Supply and Demand (WASDE) report contains and how the market interprets this information is important to understand the data set and the report's role in the market place. Understanding spread theory and what role spread theory and spread trading plays in the price discovery process for future markets is imperative. Cost of carry and the economic theory behind cost of carry and supply of storage will be discussed as well.

2.1.1 World Agriculture Supply and Demand Reports

WASDE reports are released each month and provide the market with forecasts of beginning stocks, imports, production, domestic food use, industrial use, seed use, residual use, exports, and ending stocks over the previous, current and next crop year. WASDE reports are published between the ninth and twelfth of the month. The time of day the reports are released has varied over time. From January 1985 through April 1994, monthly reports were released at 3:30 p.m. Eastern Standard Time (EST), following the close of the Chicago Board of Trade (CBOT) trading session. From May 1994 through December 2012, monthly reports were released at 8:30 a.m. EST, prior to the start of CBOT trading session. From January 2013 to current, monthly reports were released at 12:00 p.m. EST, during the CBOT trading session. These reports supply the market with United States and the rest of the World's agricultural and supply estimates, National Agricultural Statistics Service (NASS) crop production forecasts, and NASS prospective plantings and acreage estimates. This production and usage information is necessary to attract speculative interest in futures contracts and to aid in the price discovery process. Pricing signals from the futures markets are important for all participants in the supply chain–from farmers to exporters to retailers to consumers. Futures markets cannot discover price in an information vacuum – futures markets need to trade based on comprehensive and frequently published supply and demand information (McKenzie A. M., 2012). Market participants value the information in these public reports. There is a growing private industry that tries to out-forecast WASDE reports. With that said, the forecasts from these private companies are compared to the WASDE reports for accuracy.

An example of a WASDE report is presented in Appendix A. WASDE reports are published each month. Within a WASDE report are observed, estimated and projected inventory levels for each crop year. For corn, the USDA refers to a crop year as beginning September 1 and ending the following August 31. So for any given month, reported S-U levels are associated with the observed, estimated and projected amount of corn that will be carried in from the previous crop year, produced in the current crop year, used during the current crop year, and carried out to the next crop year. Observed and estimated S-U levels reflect this information from the previous and most recent two crop years. Given the historical nature of observed and estimated S-U levels, this information is likely already impounded in futures prices. In practice, the projected S-U is understood to be the driving statistic in making futures trading decisions. Projected numbers from the WASDE reports are the most valuable portion of the reports, because it is a forward looking number that provides futures traders with a window into the current crop year's supply and demand picture. So, this study will focus on the projected S-U levels.

2.1.2 Spread Trading Theory and Construction

The focus of this study is spread trading in corn future markets, so time needs to be spent understanding this section. Spread trading is not a new trading method or ideology. It has been used since the beginning of future markets to help speculators and grain merchandisers to mitigate their price volatility risk on futures trades. From a speculators point of view spread trading is a conservative trading method. Usually, spread positions will yield speculators smaller potential losses, but also smaller potential profits, than outright long or short positions established in a single futures contract month.

In its simplest form a spread describes buying one futures contract and simultaneously selling a different, but related futures contract. Spread trading takes on many forms, but this study's focus is placed on intra-market corn spreads. To set an intra-market spread a long(short) position is set in one contract month in one futures market and a short(long) position is set in a different contract month in the same futures market. A long position means to buy a contract and a short position means to sell a contract. In practice this is referred to as a calendar year spread. An example would be selling (going short) July corn futures and simultaneously buying (going long) December corn futures. Once the position is established, at some point prior to the expiration of the nearby contract the position must be reversed or offset. This is accomplished by selling the futures contract month that was initially bought and simultaneously buying the futures contract month that was initially sold. The July (old crop) December (new crop) corn futures spread – the focus of this study – is of particular interest to speculators as it is more volatile than other corn calendar spreads, making it potentially more profitable but also riskier. This is because it straddles two different crop years and as such is influenced by S-U information related to two different supply and demand periods. The July to December spread can change dramatically throughout a crop year with wide swings moving it interchangeably between a market carry (where December futures trade at a higher price level than July futures) to a market inversion (where July futures trade at higher price level than December futures).

From a grain merchandiser's perspective spread trading is an important part of generating profits from "basis trading", a grain industry term used to describe the process of buying and then selling stored hedged grain. Grain merchandisers use spreads to connect different delivery periods over the post-harvest storage period and lock in profitable margins when carrying grain. As noted above, carry spreads which occur when price of deferred futures months trade at higher levels than nearby contracts, pay and induce merchandisers or elevators to store physical cash corn. This sort of market structure helps to cover elevator storage costs. The cost-of-carry model and theory of storage explain the degree to which spreads should cover storage costs and under what type of S-U environment this will occur. The relationship between S-U levels and futures spreads in terms of cost-of-carry model and theory of storage is explained in more detail in Section 2.2.2. In contrast, merchandisers or elevators use market inversions (where nearby futures price exceeds the deferred futures price) as a signal to sell rather than store physical cash corn. In sum, futures spreads provide the grain industry with an important price discovery mechanism to guide marketing decisions.

2.1.3 Smooth Transition Autoregressive Regression Modeling

A class of smooth transition autoregressive (STAR) models (Terasvirta, 1994) is commonly used in studies attempting to model asymmetric cyclical variations and turbulent periods (Hall, Skalin, & Terasvirta, 2001); (Terasvirta, 1995); (Terasvirta & Anderson, 1992). STAR model of order p, STAR(p), can be specified as:

$$\Delta y_t = \phi_1' x_t \left[1 - G_{(s_t;\gamma,c)}\right] + \phi_2' x_t G_{(s_t;\gamma,c)} + \varepsilon_t \tag{1}$$

or alternatively:

$$\Delta y_t = \varphi_0' x_t + \varphi_1' x_t G(s_t;\gamma,c) + \varepsilon_t \tag{2}$$

where $\varphi_0 = \phi_1$ and $\varphi_1 = (\phi_2 - \phi_1)$. y_t is a dependent variable, x_t is a vector of right-hand-side variables, and $\phi_k, k = 1, 2$, are vectors of parameters; finally, ε_t is an additive error process such that $\varepsilon_t \sim iid(0, \sigma^2)$. Further, $G(s_t; \gamma, c)$ is a transition function, by construction bounded between zero and one, where s_t is a transition variable, and γ and c are, repectively, smoothness and location parameters.

In empirical studies, logistic and exponential transition functions are most frequently used forming the logistic STAR (LSTAR) and exponential STAR (ESTAR) models, respectively. Another frequently used transition function is a quadratic function, forming the quadratic STAR (QSTAR) model. These three transition functions are defined as follows:

$$G^L(S_t; \gamma, c) = (1 + exp[-\gamma(S_t - c)])^{-1} \quad (3)$$

$$G^E(S_t; \gamma, c_1, c_2) = 1 - exp[-\gamma(S_t - c)^2] \quad (4)$$

$$G^Q(S_t; \gamma, c_1, c_2) = (1 + exp[-\gamma(S_t - c_1)(S_t - c_2)])^{-1} \quad (5)$$

In the smooth transition functions γ is a nonnegative parameter. The LSTAR and QSTAR models converge to a linear autoregressive (AR) Model when $\gamma \to 0$, and a threshold autoregressive model (TAR) when $\gamma \to \infty$. The ESTAR converges to a linear AR in both cases, that is when $\gamma \to 0$ and $\gamma \to \infty$.

Often some functions of the lagged dependent variable are used as a transition variable. Alternatively, $t^* = t/T$, where T is the length of the time series, may be used as a transition variable, leading to the time-varying autoregressive (TVAR) model. Finally, the model specified in Equations 1 and 2 is a two-regime model, which may be extended to any k-regime model (see, for example, van Dijk & Farnses, 1999). In this study we use a 2-regime logistic smooth transition regression (LSTR) model, a nested version of the LSTAR model with no auto correlated lag terms.

2.2 Related Work

There have been numerous publications that have investigated the impact of WASDE report's on futures prices and their role in price discovery (Fortenbery & Sumner, 1993), (Irwin, Good, & Gomez, 2001), (Isengildina-Massa, Irwin, Good, & Gomez, 2008), (McKenzie & Holt, 2002). It is understood to be common knowledge in the market place that WASDE reports play an important role in driving prices in markets. There are alternative forecast sources market participants can use to supplement or replace WASDE reports, but WASDE reports are the industry standard for forecasting supply and demand. As mentioned before, most private forecasting firms are evaluated based on the discrepancy of their numbers versus the public forecasts.

Although a large literature has examined WASDE price effects, Dutt, Fenton, Smith and Wang (1997) is the only known study that has examined empirical behavior of old crop – new crop grain and oilseed futures spreads. Specifically they compared price changes and volatility levels between old crop – new crop spreads and intra year crop spreads (futures spreads between delivery months within the same crop year). Using standard linear statistical methods (e.g. Pearson correlations) they found that price changes in old crop – new crop spreads were less correlated and more volatile than price changes in intra year crop spreads. They argued their results were consistent with theory of storage as the more erratic pricing behavior of old crop – new crop spreads can be more often influenced by low inventory levels at the end of the old crop year. Unlike Dutt, Fenton, Smith and Wang (1997), this study focuses only on the pricing behavior of corn market old crop - new crop futures spreads, and examines the role of S-U ratios in driving spread behavior within a nonlinear-pricing framework.

2.2.1 Market Structures

Corn markets take on two futures spread structures, a carry market or an inverted market. The two different market structures incentivize producers and grain firms to either store their grain or sell it to the market. The different structures capture market agents' pricing expectations and can be at least in part explained by cost-of-carry and supply of storage models. In this study, we use S-U ratios to measure the effect of differing supply and demand levels on pricing behavior of old crop – new crop price spreads, and show how this behavior is consistent with economic theory of cost-of-carry and supply of storage.

A carry market structure occurs when the nearby futures contract month is trading at a lower price than the deferred futures contract month, referred to as a positive spread. Consider the following example, if December (DEC) futures are trading at $3.75 and March (MCH) futures are trading at $4.00, the spread between the two is 25 cents or 25 carry. In this market structure the market is signaling producers to store grain. If producers store their grain until March, they can increase their margin on their product; assuming the cost of carry is less than the margin gained from the spread and basis movement. Cost of carry is the cost of storing the grain, and reflects the opportunity cost of not selling the grain at the market (cash price) today. It is measured as the interest charge on any operating lines of credit over the storage period. Cost of carry is discussed in more detail in Section 2.2.2.

An inverted market structure occurs when nearby future contract prices trade at a premium to deferred future contract prices. Consider the example above with the numbers switched, if DEC futures are trading at $4.00 and MCH futures are trading at $3.75, the spread between the two is still 25 cents, but it is now a -25 cents or a 25 inversion. This market structure tells producers the market is demanding grain now and thus the opportunity cost of storing grain increases. An inverted market has a negative cost of storage, because the opportunity cost of not selling the grain at the market today is higher than the value of selling it a later time. In this situation the market is not rewarding or paying a premium for producers to hold and store grain.

Looking at how the corn market operates and how the market is typically structured from year to year; Corn is harvested on a seasonal basis and can be stored until the market demands the supply. The U.S. accounts for almost 40 percent of the global corn production. A typical pattern throughout the crop year is; the first quarter of the crop year inventory levels increase as new-crop is harvested and added to the inventory of what was left from last year's harvest. In the U.S. market, planting of the new corn crop begins in April and will last well into June for some areas of the country. Harvest is generally started in October and the acres are cut by the end of November. After all the acreage has been harvested and inventory is at peak levels, producers will start to sell off inventory to meet demand (Dutt, Fenton, Smith, & Wang, 1997). In a perfect crop year, with a good harvest, the market will take on a carry structure and encourage farmers to store their grain. This is expected, as the market will be flooded with new inventory and supply will be greater than demand. During the planting and harvesting months of the crop year, the old crop – new crop spread will often be at an inversion. This is expected, as inventory levels are depleted from last year's harvest, yet the market still has a demand for corn, and new crop futures prices will reflect forthcoming production and higher inventory levels in the next crop year. Encouraging farmers and merchandisers to store their grain till the market is ready is one of the greatest economic benefits associated with futures markets.

2.2.2 Cost-of-Carry, Theory of Storage, Stock-to-use Ratio and Market Expectations

Economic theory restricts the size of carry spreads and how much they can increase or widen, but the magnitude and movement of inverted spreads are not restricted. This is important when interpreting market activity. Large carry spreads in excess of storage cost represent arbitrage opportunities in the market. Explicitly, the cost-of-carry model explains that the spread difference between a nearby and a distant futures price approximates the cost (physical and opportunity cost) of storing the commodity over the time interval. Or in other words it is the return or reward to storage. This model does a reasonable job at explaining real world post-harvest spread behavior in old crop grain markets. Typically, we observe old crop carry market spreads which at least cover grain firms' storage costs. As the market takes on a carry structure, a large positive carry spread in excess of storage costs would make it attractive for market participants to act on cash-and-carry arbitrage opportunities. Cash-and-carry arbitrage involves physically delivering stored grain on short deferred futures positions, which were initiated at the beginning of a storage period along with a long nearby futures positions. Cash-and-carry arbitrage provides physical grain traders with risk-free returns. As such, as grain traders seek to exploit this opportunity, deferred futures prices will be driven down relative to nearby futures prices and the spread difference will again reflect storage costs.

In financial futures markets (e.g. interest rates) and investment commodity futures markets (e.g. gold) reverse-cash-and carry arbitrage prevents nearby futures contracts from being offered at higher prices in excess of financing charges compared with their nearby futures counterparts. However, because this trading strategy involves borrowing the physical asset – and no such market to borrow and lend agricultural consumption commodities exists – reverse-cash-and-carry arbitrage cannot be implemented in grain markets. Importantly, in terms of economic theory this means there are no implied restrictions on the size of grain futures market inversions.

The supply of storage theory as first proposed by Working (1949) explains that carry spreads should result from excess supply of old crop in the market. The greater the levels of inventory relative to current demand the greater is the physical costs associated with storing grain, the lower the opportunity costs of storing grain, and the greater the carry-spread incentive to store provided by the futures market, and the greater the supply of storage provided by physical grain traders. Conversely, the lower the levels of inventory relative to current demand the greater the inverted-spread disincentive to store provided by the futures market and the lower the supply of storage provided by physical grain traders. In the case where there is not sufficient supply the inverted market structure can increase to extreme levels. Typically, big inverted market structures are observed during drought years, big natural disaster events and potential stock-outs. In Working's (1949) seminal American Economic Review (AER) article he drew a nonlinear stylized supply-of-storage curve for wheat, which depicts an extreme market inversion – which he labels as price of wheat storage – with respect to low amounts of wheat storage supplied. Interestingly, he drew a fairly flat carry-spread structure for a wide range of moderate to high amounts of wheat storage supply. So the potential for nonlinear and asymmetric price responses in futures spreads induced by low versus high inventory levels has long been recognized, but until this study there has been no attempt to explicitly model this type of nonlinear pricing behavior. We seek to model this type of pricing behavior using an LSTR model.

The S-U ratio, which is published monthly in WASDE reports, is highly scrutinized by market traders and reflects the relative supply and demand picture for a given crop year. It is a statistic that measures the remaining expected inventory for a crop year divided by the expected inventory used for the same crop year. It has been used in a number of studies seeking to estimate the supply of storage with respect to futures spreads (Zulauf, Zhou, & Roberts, 2006). In line with supply of storage theory, the S-U ratio can indicate what the current market structure should be and what market structure to expect. At any given time a market structure can shift from one extreme to the other – carry to inversion depending on the release of new S-U numbers in WASDE reports. For example, a high S-U ratio will typically have a carry market structure. This makes intuitive sense; a higher remaining inventory level and a lower level of used inventory for a period would yield a high S-U ratio and a carry market structure. The opposite is true for an inverted market structure. An inverted market structure should have a lower S-U ratio; lower remaining inventory for the period and higher level of used inventory for the period.

3. MODELING

3.1 Linear Model

The study consisted of two different modeling approaches; linear and a non-linear model. The linear model used in the study is a standard ordinary least squared (OLS) regression and is specified as follows,

$$December/July\ Spread = \beta_0 + \beta_1 X + \varepsilon \tag{6}$$

The dependent variable is the old to new crop year spread, July (old) to December (new). β_0 is an unrestricted constant coefficient and β_1 is the coefficient for S-U ratio. ε is an normally independent and normally distributed error term. The regression model is interpreted as regressing old to new crop year spread on X, which is the projected S-U ratio. Previous research has modeled the relationship between spreads and S-U within a linear framework, and hence we used this model as a base case with which to compare the fit of our nonlinear LSTR model.

3.2 Non-Linear Model

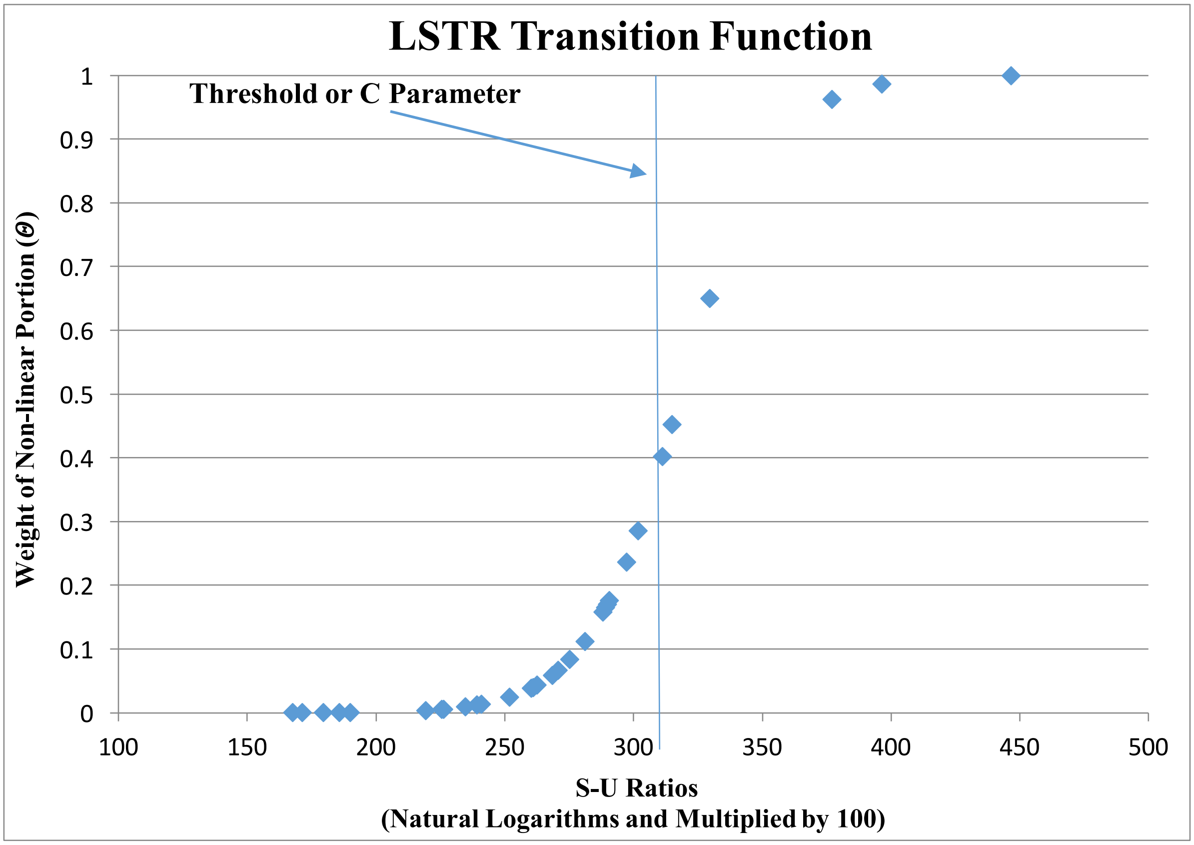
The non-linear model we estimate in this study is a logistic smooth transition regression (LSTR) model, which allows the estimated parameters to change with respect to a transition variable. In our case the transition variable is S-U ratio. So as the S-U ratio levels change from a low to high S-U regime there is a smooth nonlinear price effect on old crop – new crop futures spreads. The LSTR model is specified below.

$$December/July\ Spread = \emptyset' Z_t + \Theta Z_t G(\gamma, c, S_t) + u_t \tag{7}$$

The dependent variable is again old crop - new crop futures spread (Dec/Jul Spread), where Dec/Jul spread is the natural logarithm of the spread times 100. There is only one independent variable again, the S-U ratio. However, the LSTR model specification comprises two portions, a linear and a non-linear portion. $\emptyset' Z_t$ is the linear part and $\Theta' Z_t G(\gamma, c, S_t)$ is the non-linear portion. The linear portion of the model is similar to the OLS model, but the estimated parameters will differ from our OLS estimates as both the linear and nonlinear components are estimated simultaneously using conditional maximum likelihood. The log-likelihood is maximized numerically with JMulTi software using the iterative Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm. The model estimates a vector of parameters $\emptyset$ and Θ from a vector Zt of explanatory variables. In this study, the vector Z_{t} contains only a constant term and one variable, S-U ratio. The weight placed on the Θ parameter vector varies with the transition variable contained in the non-linear portion of the model.

The non-linear portion of the model, $\Theta' Z_t G(\gamma, c, S_t)$, can be further illustrated as $G(\gamma, c, S_t) = (1 + exp\{-\gamma \prod_{k=1}^{K}(S_t - C_k)\})^{-1}$. $G(\gamma, c, S_t)$ is referred to as the transition function and is bounded in value between 0 and 1. With *K*=1, The model estimates what is called a transition variable, S_t, which for this model, as already noted, is the S-U ratio. For *K*=1, the parameters $\emptyset + \Theta\ G(\gamma, c, S_t)$ change monotonically as a function of S_t from $\emptyset$ to $\emptyset + \Theta,$ and the model is capable of characterizing asymmetric behavior within two distinct regimes. In practice, although S-U ratios are reported every month in WASDE reports, they may not change every month or trend slowly over time and hence any model that specifies S-U as an independent variable and which is sampled monthly will likely suffer from autocorrelation. Although, specifying lagged S-U terms in our LSTR model would be a valid model specification to account for this autocorrelation, we instead chose to sample S-U on a yearly basis to avoid any estimation issues associated with autocorrelation. Specifically, only projected S-U values observed in January WASDE reports are sampled for modeling purposes. The January WASDE report is used as it contains final revised projections of current old crop year production numbers, and so provides an accurate old crop supply picture with which to measure an accurate relationship between S-U and futures spreads. The January WASDE reports are a good representation of the sample period based on the summary statistics in Section 4.1.1 in Table 1. The nonlinear part or transition function part of the model also contains a threshold variable C and a slope variable γ. The threshold variable is what establishes two different regimes of S-U ratios; a low S-U and a high S-U. As the transition variable and S-U ratios change from low to high values, the LSTR model can describe pricing processes whose dynamic properties are different in low S-U ratio environments compared to high S-U ratio environments. The transition from one regime to the other is a smooth transition, and as such our model does not estimate a sudden change in parameter value weights but instead is governed by the slope or rate of change γ of the transition function. The $G(\gamma, c, S_t)$ transition function of the LSTR model is illustrated graphically in Figure 1 below with S-U ratios transformed into natural logarithms and multiplied by 100.

Figure 1: Non-linear transition function, $G(\gamma, c, S_t)$



3.3 Trading Strategy Simulation

After the models' parameters have been estimated the S-U ratio values can now be used to forecast spreads. The process is identical for both the OLS and LSTR models. The forecasted spreads are considered market signals, signaling a carry or an inverted market structure as well as the size of the spread. The primary objective for the trading strategy is to buy one spread low and sell the other spread high. The trading strategy begins each crop year in September and ends the following July. Every month when the WASDE report is released the new S-U ratios are then imputed into the model and a forecasted December to July Spread is generated. The generated spread is compared to actual market spreads at the time (one trading day after the report is released). If the model generated spread forecast predicts the current actual market spread should be more positive or more of a carry, then nearby July contract is sold and distant December contract is bought. Similarly, if the model generated spread forecast predicts the current actual market observed spread should be more negative or more of an inversion, then nearby July contracts are bought and distant December contracts are sold. Here are some examples. If a current market spread is +5 carry and our model forecasted market spread is +17 carry, then this tells us that our model predicts spreads to increase and take on a wider carry market structure. The strategy in this example would be buy the distant December futures contract and sell the nearby July contract. This strategy represents the primary objective of buying low and hopefully selling high at a later date. If the opposite occurs the strategy is reversed; if current market spread is +5 carry and the forecasted market spread is -17 inversion, then this tells us that our model predicts spreads will decrease and take on an inverted market structure. The strategy for this example would be buy the nearby July futures contract and sell the distant December futures contract. Again, this strategy stays true to the primary objective of initially selling the spread high and hopefully later buying the spread low.

As mentioned in Section 2.1.1, WASDE reports are released each month. As each report is released the strategy is re-evaluated. All spread positions are liquidated each year at the release time of the July WASDE report as the July futures portion of the spread expires. Each year in the sample period, total profits or losses (ignoring transaction or trading costs) are calculated. Average yearly profits or losses for each model generated strategy are calculated over the whole sample period and standard statistical tests are applied to determine if profits or losses are statistically different from zero.

4. RESULTS AND ANALYSIS

4.1 Results

The data used for the study, the results of the models and the trading strategy will be discussed individually in the proceeding sections. Each of the models yielded different results. The OLS model supported a positive linear relationship between S-U ratios and spreads. The LSTR model yielded a strong non-linear relationship between S-U ratios and spreads. The simulated trading strategy did not result in a statistically positive crop year profit on average.

4.1.1 Data

There are only two sources for data in this study, the United States Department of Agriculture and the Chicago Board of Trade. The sample period for the study is January 1985 through April 2015. The WASDE reports are sourced from the United States Department of Agriculture archived reports. Within this sample period, a total of 369 WASDE reports were released and 31 January reports were used to sample S-U numbers as inputs for linear OLS and LSTR models. 327 of the reports for the September through July months each year were used to compute S-U ratios and forecast spread values. In Appendix C a graph of S-U ratios over the sample period is displayed. Futures pricing data were sourced from the Chicago Board of Trade. The daily closing market values for July and December future contracts for the sample period were collected and used to compute the spread values. The futures price spreads and S-U ratios were transformed into natural logarithms and multiplied by 100. Thus our transformed spread data measures the percentage difference between futures prices. In Appendix D a graph of the old crop – new crop spreads over the sample period is displayed. Below, Table 1 displays summary statistics for the data in the sample period in actual values, before the values are transformed to natural logarithmic and multiplied by 100.

Table 1: Summary Test Statistics for the Sample Period, January 1985 to April 2015

Sample Period, January 1985 through April 2015, Summary Statistics				
	Minimum	Maximum	Mean	Standard Deviation
S-U	4.277	89.405	18.545	14.970
Old Crop – New crop Spread	-35.694	10.112	-1.263	8.073

January WASDE Reports, January 1985 through April 2015, Summary Statistics				
	Minimum	Maximum	Mean	Standard Deviation
S-U	5.343	86.996	18.503	16.279
Old Crop – New crop Spread	-21.172	8.550	-1.674	7.948

The first section of Table 1 displays summary statistics for the sample period. The minimum S-U ratio is 4.277 and the maximum S-U ratio is 89.405. The mean for the S-U ratios is 18.545 and the standard deviation is 14.970. The old crop – new crop spread (July – December) minimum is -35.694 and the maximum is 10.112. The mean for the old crop – new crop spread is -1.263 with a standard deviation of 8.073. The second section of Table 1 displays summary statistics for the January WASDE reports in the sample period. There are a total of 31 January reports. The minimum S-U ratio is 5.343 and the maximum S-U ratio is 86.996. The mean for the S-U ratios is 18.503 and the standard deviation is 16.279. The old crop – new crop spread (July – December) minimum is -21.172 and the maximum is 8.550. The mean for the old crop – new crop spread is -1.674 with a standard deviation of 7.948.

4.1.2 OLS Results

Estimated coefficient values for the OLS regression are presented in Table 1. The coefficient values are significantly different from zero based on the standard t-stat test statistic and residual diagnostic tests for first order autocorrelation and heteroscedasticity indicate the model is well specified.

Table 2: OLS Model Coefficients and Test Statistics

	Coefficient Estimate	Standard Deviation	t-Stat	p-Value
Constant	-18.93	5.50	-3.44	0.002
S-U	0.06	0.02	3.22	0.003

Test Statistics	Stat	p-Value
Ljung Box Q-Statistics (Lag 1)	3.35	0.07
Breusch-Pagan Heteroscedasticity Test Chi-Squared (1)	0.18	0.67
Number of observations - 31		

The results show a significant positive linear relationship between S-U ratios and spreads are consistent with previous research. The results of the OLS regression can be interpreted as a 1% increase in S-U ratios, results in a 0.06% change in old crop – new crop corn spreads. Based upon closing July 2016 and December 2016 CBOT corn futures prices reported on 4/15/16, the current spread in cents/bushel(bu) is a 7 cents/bu carry (July is 380 cents/bu and December is 387 cents/bu). So a 1% increase in S-U ratio would result in 0.06% or a 0.42 cents/bu increase in the spread. It is not unusual for S-U ratios to change by as much as 10% over a September to July crop year period (e.g. over the most recent full crop year in our sample (September 2013 – July 2014) S-U ratio fell by 8%). So if S-U ratio increases 10% our OLS model based on current spread values would have predicted a 0.6% or 4.2 cents per bushel increase in spread. These results are consistent with the supply of storage theory that was discussed in Section 2.2.2, where a higher S-U ratio leads to a larger positive carry spread and a lower S-U ratio leads to a lower carry spread or a larger negative inversion.

4.1.3 LSTR Results

The estimated coefficient values for the LSTR model can be seen in Table 2. The coefficient estimates are significantly different from zero at conventional levels based on the standard t-stat test statistics, with the exception of the coefficient for the slope, which is significant at the 12% level.

Table 3: LSTR Model Coefficients and Test Statistics

Linear

	Coefficient Estimate	Standard Deviation	T-Stat	P-Value
Constant	-50.01	10.74	-4.66	0.0001
S-U	0.20	0.05	4.00	0.0005

Non-Linear

	Coefficient Estimate	Standard Deviation	T-Stat	P-Value
S-U	-0.08	0.03	-2.67	0.0071
Gamma	3.53	2.16	1.63	0.1137
C	318	9.81	32.42	0.0000

Test Statistics	F-Stat	P-Value
Generalized Godfrey F-Test For No Autocorrelation F(1,24)	0.935	0.344
Number of observations -31		

The coefficient results for the LSTR model cannot be directly interpreted in the way the OLS model's coefficients were interpreted. This is because the weights applied to the coefficients for the nonlinear transition function vary depending on S-U regime, either high or low, and the linear and nonlinear coefficients jointly predict the percentage change in futures spreads brought about by a percentage change in the S-U ratio. Instead we interpret LSTR results by graphing and comparing the in-sample model forecasts against OLS forecasts. This analysis is presented and discussed in Section 4.2 below. Results of a generalized Godfrey test presented at the foot of Table 2 reveal our model does not suffer from first order autocorrelation.

A statistical test proposed by Terasvirta (1994, 1998) tests whether the preferred model choice is linear or of the nonlinear LSTR type. This is essentially a test where the null hypothesis is that $\gamma = 0$. Note from equations (1) and (2) when $\gamma = 0$ our LSTR model reduces to the simple linear OLS model specification. However, equations (1) and (2) are only identified under the alernate hypothesis (Ha: $\gamma > 0$), which renders the usual asymptotic distribution theory of the classic test statistics invalid (Lutkepohl, Terasvirta, and Wolters, 1999). So following Terasvirta (1994, 1998) we test the null hypothesis of linearity against LSTR nonlinearity by testing H_0: $\delta_1 = \delta_2 = \delta_3 = 0$ in the auxiliary regression using an $F_{(6,22)}$ test (Terasvirta, 1998).

$$Dec/Jul\ Spread = \emptyset' Z_t + \delta_0' Z_t + \delta_1' Z_t S_t + \delta_2' Z_t S_t^2 + \delta_3' Z_t S_t^3 + v_t \tag{8}$$

The p-value of 0.0006 for the resulting F-test clearly revealed that the null hypothesis of linearity was rejected and hence LSTR is the preferred model.

4.1.4 Simulated Trading Strategy Results

The simulated trading strategy results are evaluated based on the average amount of profit generated from the spreads at the end of each season. Both of the models average a loss over the 31 years in the sample period. The LSTR model yielded 6.13 cents per bushel loss. The OLS model yielded 1.62 cents per bushel loss. There are more test statistics for the trading strategies displayed in Appendix B. While the strategies did not produce a profit at the end of the season all is not lost.

4.2 Analysis

First, we discuss our simulated trading results. Based on the extensive literature stating how efficient futures markets are at adjusting to new market information, it was unlikely a trading strategy would be developed to outperform the market, without access to predicted S-U values prior to WASDE release times. Our models make spread forecasts based upon S-U inputs revealed in WASDE reports and these forecasts are compared to day after release actual market spreads and appropriate buy or sell spread strategies are then enacted. So, it is likely that actual futures spreads have already adjusted to S-U information contained in the WASDE reports making it difficult for our models to beat the market.

Next, we discuss our OLS and LSTR model results. The positive linear relationship between the S-U ratios and the old crop - new crop spreads was expected. Previous studies have modeled similar variables and found evidence of this relationship. Most interestingly, the non-linear relationship between the S-U ratios and the old crop - new crop spreads clearly shows that futures market responses differ depending upon the level of S-U and that the price responses are consistent with what we would expect based upon cost-of-carry and supply of storage theory. Figure 2 below displays this relationship graphically.

Figure 2: Spread, Models and S-U Ratio, 1985 to 2015

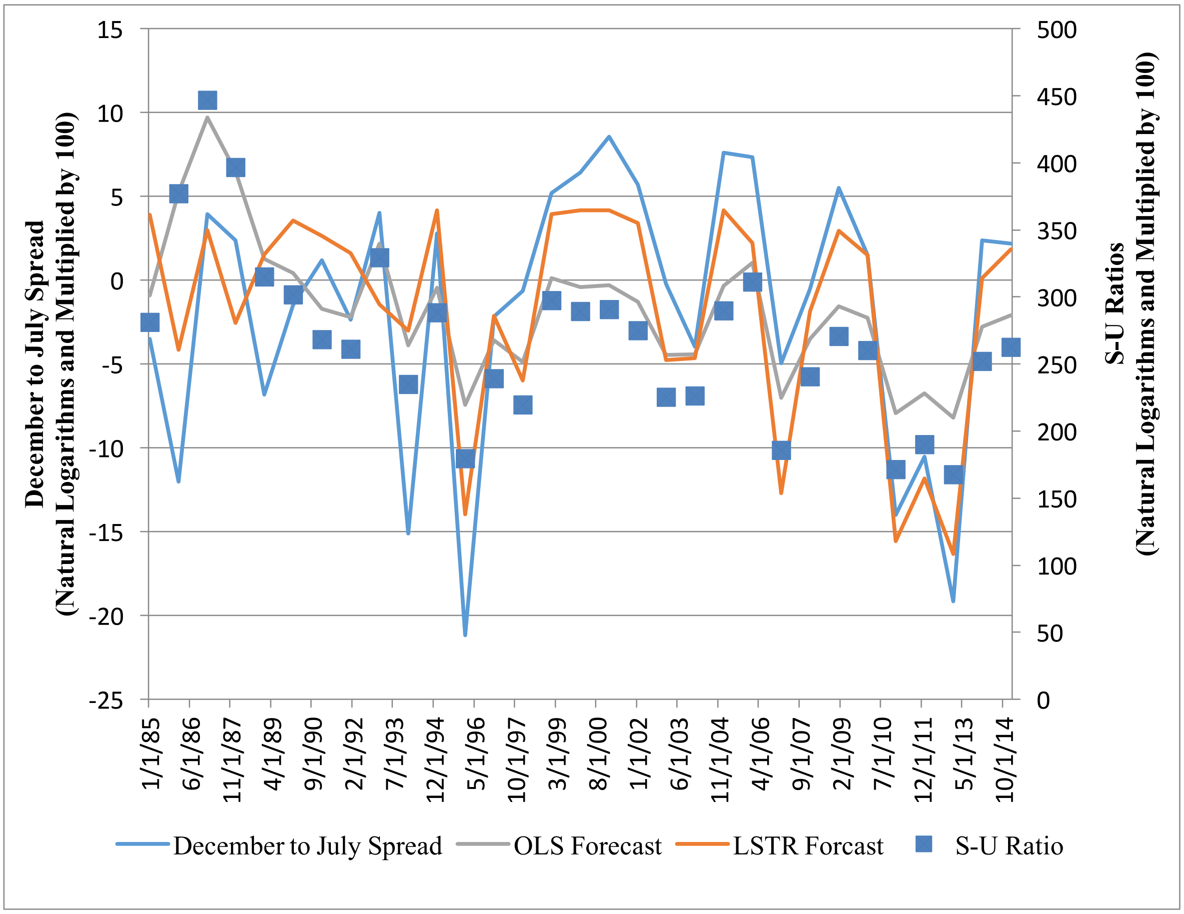


Figure 2 displays real market asymmetric behavior for old crop - new crop year spreads and S-U ratios for the sample period. It can be seen that markets move frequently between carries and inversions across the sample years and that there is a tendency for carry-markets to be associated with relatively high S-U numbers and for inversions to be associated with low S-U numbers. Figure 2 also displays the OLS and LSTR models' forecasted values. The LSTR model does a superior job at capturing spread behavior over the sample period. The standard deviation of LSTR model residuals is only 4.8 compared to the standard deviation of OLS model residuals of 6.8. The OLS model for almost every observation in the sample period under or over forecasted market structure, and forecasts are not always consistent with the economic theory described in Section 2.2.1. For example, logarithmic S-U ratios values below 200; economic theory states that a small S-U ratio would yield a large inverted market structure. The LSTR model does a far superior job at capturing the big market inversions versus the OLS model. This is consistent with economic theory, which places no theoretical restriction on how large market inversions can get when inventory levels are low. Looking at the opposing S-U ratio regime; S-U values above 350. The OLS model predicts market carries well above actual market activity. In contrast, the LSTR model better captures actual market structure. This is consistent with economic theory, which places an artificial ceiling on how high market carries can rise. The economic theory of storage was first introduced in the literature over 60 years ago (Working, 1949). To date, there has been no attempt to model the pricing asymmetries and nonlinearities that this economic theory would predict. Our LSTR model represents the first empirical work to at least capture some of this pricing behavior.

5. CONCLUSIONS

5.1 Contributions

This study did not yield the next big profitable trading strategy, but it does make a big contribution to the literature. It shows there is a strong non-linear relationship between S-U ratios and spreads in corn futures market. Importantly, this study extends the literature that has historically only focused on the linear relationship between futures spreads and supply and demand.

This study sets the ground work for future studies to continue testing non-linear relationships between commodity prices and other factors impacting supply and demand such as government farm policy, international trade policy, and weather events. Nonlinear modeling techniques could be applied to other agricultural markets to determine if similar nonlinear pricing behavior describes non-storable commodities. In terms of forecasting, a higher frequency LSTAR model could be estimated using futures spread lags and S-U lags. Also, from a forecasting standpoint it would be interesting to determine if an LSTAR type model could generate speculative trading profits using privately forecasted S-U ratios observed prior to publicly released WASDE S-U ratios.

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APPENDIX A. WASDE EXAMPLE

April 2015

WASDE - 540 - 12

U.S. Feed Grain and Corn Supply and Use 1/

FEED GRAINS	2012/13	2013/14 Est.	2014/15 Proj. Mar	2014/15 Proj. Apr
		Million Acres		
Area Planted	109.9	109.9	103.4	103.4
Area Harvested	96.6	98.1	93.0	93.0
		Metric Tons		
Yield per Harvested Acre	2.95	3.74	4.05	4.05
		Million Metric Tons		
Beginning Stocks	27.8	23.5	34.3	34.3
Production	285.1	366.9	376.9	376.9
Imports	6.4	3.0	2.9	2.9
Supply, Total	319.4	393.4	414.1	414.2
Feed and Residual	115.1	133.3	139.9	137.9
Food Seed & Industrial	160.1	171.4	172.7	172.3
Domestic, Total	275.2	304.7	312.6	310.2
Exports	20.7	54.4	53.6	54.9
Use, Total	295.8	359.1	366.2	365.1
Ending Stocks	23.5	34.3	47.9	49.1
CCC Inventory	0.0	0.0	0.0	0.0
Free Stocks	23.5	34.3	47.9	49.1
Outstanding Loans	0.8	2.0	5.9	5.9
CORN				
		Million Acres		
Area Planted	97.3	95.4	90.6	90.6
Area Harvested	87.4	87.5	83.1	83.1
		Bushels		
Yield per Harvested Acre	123.1	158.1	171.0	171.0
		Million Bushels		
Beginning Stocks	989	821	1,232	1,232
Production	10,755	13,829	14,216	14,216
Imports	160	36	25	25
Supply, Total	11,904	14,686	15,472	15,472
Feed and Residual	4,315	5,036	5,300	5,250
Food, Seed & Industrial 2/	6,038	6,501	6,595	6,595
Ethanol & by-products 3/	4,641	5,134	5,200	5,200
Domestic, Total	10,353	11,537	11,895	11,845
Exports	730	1,917	1,800	1,800
Use, Total	11,083	13,454	13,695	13,645
Ending Stocks	821	1,232	1,777	1,827
CCC Inventory	0	0	0	0
Free Stocks	821	1,232	1,777	1,827
Outstanding Loans	32	76	230	230
Avg. Farm Price ($/bu) 4/	6.89	4.46	3.50 - 3.90	3.55 - 3.85

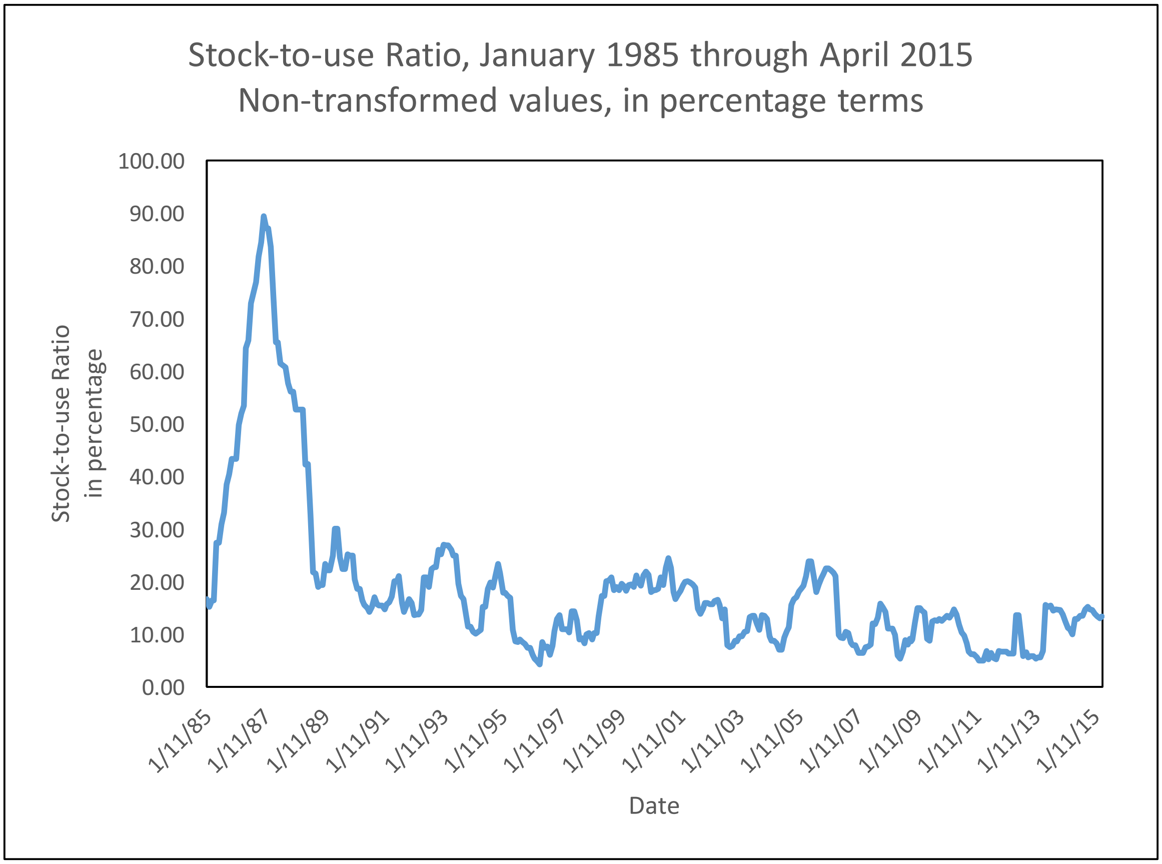
Note: Totals may not add due to rounding. 1/ Marketing year beginning September 1 for corn and sorghum; June 1 for barley and oats. 2/ For a breakout of FSI corn uses, see Feed Outlook table 5 or access the data on the Web through the Feed Grains Database at www.ers.usda.gov/data-products/feed-grains-database.aspx. 3/ Corn processed in ethanol plants to produce ethanol and by-products including distillers' grains, corn gluten feed, corn gluten meal, and corn oil. 4/ Marketing-year weighted average price received by farmers.

APPENDIX B. TRADING SIMULATION TEST STATISTICS

OLS Model	
Average	-1.6167
t-Stat	-0.2535
Standard Deviation	34.9332
N	30
p-Value	0.4008

LSTR Model	
Average	-6.1250
t-Stat	-0.9459
Standard Deviation	35.4682
N	30
p-Value	0.1760

APPENDIX C. STOCK-TO-USE RATIOS, JANUARY 1985 THROUGH APRIL 2015



APPENDIX D. OLD CROP – NEW CROP SPREAD, JANUARY 1985 THROUGH APRIL 2015