THREE ESSAYS ON DYNAMICS IN BEEF CATTLE SUPPLY AND PRICES

by

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(Under the Direction of J. Scott Shonkwiler)

ABSTRACT

In this study, we focus on the dynamics in supply and prices of livestock, specifically beef cattle. Beef cattle have a unique and complex lifecycle. Our research results will provide market participants with informative implications thus helping form a more efficient livestock market. The dissertation is composed of three chapters, where we examine the industry from a top-down aspect: from a macro national market, to regional markets, and finally to micro auction sales.

In Chapter I, we examine the dynamics of beef cow supply and the existence of the cattle cycle in light of the shift in the structure of cattle finishing and herd management during the last fifty years. Both first- and second-order stochastic cycle models were used to examine semi-annual and annual U.S. beef cow inventory series. Empirical results obtained by both approaches suggest a significant lengthening cattle cycle of over 15 years, possibly indicating that cycles are disappearing.

In Chapter II, we expand our discussion on the dynamics cattle prices from time series horizon to spatial dimension. Specifically, we examine the cointegration of cattle prices over regions by proposing a simple procedure for incorporating a flexible transition function into an economic indicator-controlled smooth transition autoregressive (ECON—STAR) model to evaluate market dynamics. The empirical results show that these markets have been highly integrated when excess supply exists, but when cattle inventories decrease, the market pattern becomes very regionally segmented.

In Chapter III, we take a micro look at one of the most common price discovery mechanisms in livestock markets, the auction, where we are interested in the sale order effect on the winning prices. We empirically confirmed the existence of the declining price anomaly by introducing the Generalized Extreme Value theory framework. Empirical results indicate that the unit price difference between the first and the last lot sold ranges from $7.82 to $2.31, depending on the average animal weight in that lot. Moreover, we found that the buyer's maximum valuation on the subsequent object actually declines as he wins more objects, which provides a plausible explanation for the declining price anomaly.

INDEX WORDS: cattle cycle, stochastic cycle, smooth transition autoregressive model, sequential auction, declining price anomaly

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CHAPTER 1

FIRST– AND SECOND – ORDER STOCHASTIC CYCLE MODELS OF U. S. BEEF COW INVENTORIES

1. Introduction

The dynamics of beef cattle supply and the existence of cattle cycles have been widely researched topics in the last four decades. The work of Jarvis (1974) was first to treat beef cows in the context of capital goods and recognized that increasing beef prices can actually lead to reduced slaughter in the short run. This approach influenced empirical approaches to modeling the beef cattle herd such as formulated by Rucker, Burt, and LaFrance (1984) and stimulated a theoretical treatment of the dynamics of livestock production by Rosen (1987). Rosen, Murphy, and Scheinkman (1994) specifically addressed the existence of cattle cycles. More recently Aadland (2004) constructed a model to describe the putative 10 year cattle cycle by assuming that producers maximize a discounted stream of future profits subject to biological constraints and market forces.

This analysis reconsiders the dynamics of beef cow inventories in light of the shift in the structure of cattle finishing and herd management during the last fifty years. Nerlove and Fornari (1998) have criticized the Rosen et al. (1994) approach for not recognizing the structural change that occurred in the beef cattle market during the 100 plus years of their analysis. Nerlove and Fornari specifically cited changes in cattle finishing, breeding practices, and beef cattle genetics as causes for structural change. The presence of large commercial feedlots has industrialized the production of fed beef. Feedlot operators have the skill and resources to manage production and risk by taking positions in futures markets for feeder cattle, fat cattle, and feed grains. Currently, almost 90% of steers and heifers slaughtered are supplied by feedlots with over 1000 head capacity. Cow-calf operations have benefitted from increasing productivity (Marsh, 1999), research regarding optimal feeding schedules (Hennessy, 2006), and the education programs of extension specialists across the nation. Just as Holt and Craig (2006) speculated that continuous farrowing and total confinement operations may have shortened and dampened the hog cycle, the changing structure of beef production may have impacted the cattle cycle in a similar manner.

Consider the figure below which plots trend and seasonally adjusted standardized semi-annual beef cow inventories and similarly adjusted standardized semi-annual feeder steer/corn price ratios from 1973 to 2015. Since 1995, the number of beef cows (trend and seasonally adjusted) appears to have little cyclicality. This stands in stark contrast to the cyclical pattern given in Figure 1 of Aadland (2004, p.1978) using data from the 1930's to the late 1990's.

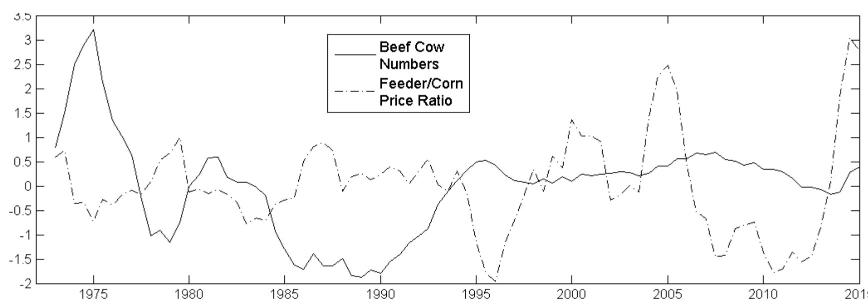

Figure 1 Trend and Seasonally Adjusted Beef Cow Numbers and Feeders Steer/Corn Price Ratio

2. The Approach

To understand the dynamics of the U. S. beef cattle herd we examine both beef cattle inventories and feeder steer prices using semi-annual data. Building on the seminal article by Jarvis (1974), a number of studies have recognized that the value of a cow is largely determined by the value of her offspring (Rucker et al., 1984; Paarsch, 1985; Marsh, 1999; Aadland, 2004) and her salvage (slaughter) value. As Aadland has succinctly stated: "A female animal has a dual value—she is valued both as a consumable product today and simultaneously as a calf-making machine over her effective lifetime" (p.1986). The net present salvage value of a cow, of course, depends on her productive lifespan, the discounted future value of her offspring, and her discounted slaughter value. Using the decision maker of Schulz and Gunn (2016) a current estimate is that the net present salvage value of a young cow is about 17% of her total discounted present value. Thus current and expected feeder cattle prices should be the primary determinant of a cow's value.

Therefore, the price most relevant to the decision of herd size is that of feeder cattle and we choose to use the Oklahoma City price for 550 pound steers. This price is normalized by the price of corn (Kansas City) to reflect the value of the calf to finishers and is consistent with the approach of Holt and Craig (2006). Both series are semi-annual data, specifically cow inventories data are point-in-time counts in January and July each year. The beef cow numbers of January are based on survey data and the mid-year numbers are derived from market information. Notice that the feeder steer/corn price ratio tends to exhibit more cyclical behaviour than inventories and also exhibits some counter-cyclical tendency relative to beef cow numbers.

Our analysis of the two time series begins with unit root tests. After creating lags of cow herd (in millions of animals) and the feeder steer/corn price ratio we have 75 semi-annual observations from January 1, 1978 to July 1, 2015. The KPSS test, the augmented Dickey-Fuller test, and the Phillips-Peron test indicated that each series is integrated of order 1. Residual based cointegration tests failed to find a cointegrating relationship between the two series under a number of alternative specifications employing polynomials in trend and the semi-annual dummy (1 for January-June, zero otherwise). Given the lack of a contemporaneous relationship, a vector autoregression analysis was undertaken. The results for the models are reported in Table 1 and all specifications include trend and seasonal terms.

Table 1 VAR Results with Time Trend and Semi-annual Dummy

MODEL	LOG LIKELIHOOD	AIC	BIC
VAR 6:	-258.81	573.62	638.51
VAR 5:	-260.49	568.98	624.60
VAR 4:	-265.21	570.42	616.77
VAR 3:	-268.79	569.58	606.66
VAR 2:	-272.68	569.36	597.17
VAR 1:	-288.34	592.68	611.22
LR TESTS	P-VALUE		
VAR 5 vs VAR 6	0.500		
VAR 4 vs VAR 5	0.051		
VAR 3 vs VAR 5	0.035		
VAR 2 vs VAR 5	0.018		

Based on the LR (likelihood ratio) tests and the AIC we select a VAR 5 to represent the system. This model revealed that the feeder steer/corn price ratio may Granger cause cow numbers, since a test of the contrary yielded a p=0.0615. But we found evidence that cow numbers did not Granger cause prices (p=0.335). This is consistent with Shonkwiler and Hinckley (1985) where current feeder calf prices are based on the economics of cattle finishing, not on the size of the cow herd.

Recalling that a VAR with deterministic components can be written as $\mathrm{A(L)}\boldsymbol{y_t} = \mathrm{B}\boldsymbol{x_t} + \boldsymbol{\epsilon_t}$, by the fundamental dynamic equation we have $|\mathrm{A(L)}|\, \boldsymbol{y_t} = \mathrm{Adj(A(L))}(\mathrm{B}\boldsymbol{x_t} + \boldsymbol{\epsilon_t})$. Thus the series in $\boldsymbol{y_t}$ must share the same long run dynamics given by $|\mathrm{A(L)}|$. A restricted VAR 5 provided four pairs of complex conjugate roots of $|\mathrm{A(L)}|$ which implied cycles of 2.68, 2.888, 10.50, and 12.86 semi-annual periods. Analysis of the VAR 2 model (which would be selected using the BIC criterion) showed a single pair of complex conjugate roots with an implied cycle length of 17.12 semi-annual periods. Clearly there is no agreement on a cycle length. Further the irregular patterns in both series suggest that the amplitude and phase of each series has been evolving over time. To address these issues we investigate a stochastic cycle (Harvey, 1989; Parker and Shonkwiler, 2014) model which allows i) an analysis of non-stationary data; ii) direct estimation of cycle length; and iii)shifting phase and changing amplitudes.

3. The Basic Stochastic Cycle Model

For a single time series, the model is specified to be a random walk (with drift) with a stochastic cycle (Harvey).

(1) $y_t = \mu_t + \psi_t + x_t\delta + \varepsilon_t$

(2) $\mu_t = \mu_{t-1} + \beta + \eta_t$

(3) $\psi_t = \rho\{\cos(\lambda)\,\psi_{t-1} + \sin(\lambda)\,\psi^*_{t-1}\} + \kappa_t$

(4) $\psi^*_t = \rho\{-\sin(\lambda)\,\psi_{t-1} + \cos(\lambda)\,\psi^*_{t-1}\} + \nu_t$

Here μ_t and ψ_t represent dynamic unobservables associated with a random walk (with drift β) and a cyclical process (with frequency λ). The coefficient ρ is termed the damping factor and $\rho = 1$ if the cyclical process is non-stationary. The error processes $\varepsilon_t, \eta_t, \kappa_t$, and ν_t are assumed to be iid normal with variance-covariance matrix

$$\begin{bmatrix} \sigma^2_\varepsilon & 0 & 0 & 0 \\ 0 & \sigma^2_\eta & 0 & 0 \\ 0 & 0 & \sigma^2_\kappa & 0 \\ 0 & 0 & 0 & \sigma^2_\nu \end{bmatrix}$$

The initial conditions ψ_0 and ψ^*_0 determine the initial amplitude and phase shift of the series and μ_0 denotes the initial level of the series which typically can be set at y_0.

Parker and Shonkwiler (2014) show that the reduced form of the model can be written in terms of the observable process y_t, the unknown parameters, and the error processes:

$$(5)\ \Delta y_t = 2\rho\cos\lambda\Delta y_{t-1} - \rho^2\Delta y_{t-2} + \beta^* + \eta_t - 2\rho\cos\lambda\eta_{t-1} + \rho^2\eta_{t-2} + \Delta\kappa_t - \rho\cos\lambda\Delta\kappa_{t-1} + \rho\sin\lambda\Delta\nu_{t-1} + \Delta\xi_t - 2\rho\cos\lambda\Delta\xi_{t-1} + \rho^2\Delta\xi_{t-2}$$

where Δ denotes the (first) difference operator and $\xi_t = x_{t\delta} + \varepsilon_t$. In time series parlance the series is a type of ARIMA(2,1,2) process. This representation is valid when y_t follows a random walk, i.e. $\sigma_\eta^2 > 0$ and consequently the series must be first differenced to achieve stationarity. If this is not the case, the model with $\sigma_\eta^2 = 0$ simplifies to

$$(6)\ y_t = 2\rho\cos\lambda y_{t-1} - \rho^2 y_{t-2} + \beta t + \kappa_t - \rho\cos\lambda\kappa_{t-1} + \rho\sin\lambda\nu_{t-1} + \varepsilon_t - 2\rho\cos\lambda\xi_{t-1} + \rho^2\xi_{t-2}$$

or a type of ARMA(2,2) process with constant trend. An additional simplification of the dynamic process occurs when all the noise in the system is due to the stochastic cycle. In this case $\sigma_\varepsilon^2 = 0$, and then

$$(7)\ y_t = 2\rho\cos\lambda y_{t-1} - \rho^2 y_{t-2} + \beta t + \kappa_t - \rho\cos\lambda\kappa_{t-1} + \rho\sin\lambda\nu_{t-1} - 2\rho\cos\lambda x_{(t-1)}\delta + \rho^2 x_{(t-2)}\delta.$$

a) Univariate Results

Setting μ_0 equal to y_0 and imposing the customary restriction (Harvey, p.39) that $\sigma_\kappa^2 = \sigma_\nu^2$ for the cow herd size, we found that both σ_ε^2 and σ_η^2 converged to zero under maximum likelihood estimation of the stochastic cycle model. Imposing these restrictions and restricting ψ_0 to zero and ρ to one gave a model with 4 fewer parameters. A likelihood ratio test of the 5 restrictions yielded $X^2 = 3.04$ ($p \approx .551$); the approximate p-value represents the fact that 2 of the restrictions involved parameters on boundaries of the parameter space. However, examination of the residual correlogram indicated temporal dependence among the residuals and this was confirmed by a Ljung-Box Q-test with 12 lags ($p = 0.013$). This was addressed by adding a fourth lag of the cow herd as this yielded a Ljung-Box Q-test having a p-value of 0.628 over 12 lags. The results are reported in Table 2.

The highly significant coefficient on the semi-annual dummy variable (DV) shows that the cow herd tends to be larger on July 1 than on January 1. The estimate of β can be interpreted as a decreasing trend in beef cow numbers. The estimate of λ implies a cattle cycle of $\frac{2\pi}{\hat{\lambda}}$, about 32.5 periods or 16.24 years. Using the delta method, we find an approximate asymptotic 95% confidence interval for the cycle of 12.4 to 20.1 years.

Table 2 Univariate Model – Cow Herd

Parameter/ Coefficient	Estimated Value	Robust Std. Error	z-Value
DV	0.7524	0.0443	16.998
$\sigma_\kappa = \sigma_\nu$	0.3131	0.0397	7.891
λ	0.1935	0.0234	8.278
β	-0.0869	0.0083	-10.53
ψ_0^*	2.182	2.4099	0.905
$y_{1,t-4}$	-0.1238	0.0594	-2.085
Log likelihood	-30.11		

A similar unrestricted model is specified for the feeder steer/corn price ratio. Again both σ_ε^2 and σ_η^2 converged to zero. Imposing the same four restrictions as before ($\sigma_\varepsilon^2 = \sigma_\eta^2 = 0;\ \psi_0 = 0;\ \rho = 1$) resulted in a likelihood ratio test statistic of $X^2 = 4.94\ (p \approx .291)$. Analysis of the residual correlogram for this model showed a spike at the fourth lag, so the model was re-estimated by including y_{2t-4}. For this model of the feeder steer/corn price ratio reported in Table 3, the Ljung-Box Q-test had a p-value of 0.754 over 12 lags.

The cattle cycle implied by this model is 26.6 periods or 13.3 years. The approximate asymptotic 95% confidence interval spans from 7 to 19.6 years and thus is seen to overlap much of the confidence interval obtained from the cow herd model.

Table 3 Univariate Model – Feeder Steer/Corn Price Ratio

Parameter/ Coefficient	Estimated Value	Robust Std. Error	z-Value
DV	4.5269	0.7788	5.813
$\sigma_\kappa=\sigma_\nu$	5.3403	0.4411	12.108
λ	0.2362	0.0572	4.133
β	0.4965	0.2059	2.411
ψ^*_0	1.9118	16.2726	0.117
$y_{2,t-4}$	-0.3913	0.1463	-2.675
Log-likelihood	-241.98		

b) The Bivariate Stochastic Cycle Model

These findings lead naturally to considering the estimation of the cattle cycle using both the beef cow herd series (y_1) and the feeder steer/corn price series (y_2). We first estimate the models simultaneously imposing the restriction that each stochastic cycle shares the same λ. Then we investigate the interrelationships between the stochastic cycles. This is accomplished by augmenting the state equation for the cow herd as follows $y_{1,t} = \mu_{1,t} + \psi_{1,t} + \alpha\psi_{2,t-s} + x_{(1,t)}\delta + \varepsilon_{1,t}$; where $\psi_{2,t-s}$ is the cyclical component associated with the feeder/corn price ratio.

Joint estimation of the stochastic cycle models reported in Table 2 and Table 3 under the restriction of a common λ parameter generated a log likelihood of -272.41 at convergence and a corresponding likelihood ratio test statistic of $X^2 = 0.63$ with one degree of freedom. Estimated parameters and associated standard errors were largely unchanged from those reported in Tables 2 and 3. The estimate of λ was 0.2009 with robust standard error of 0.0236 which indicates a cattle cycle of 15.64 years with an associated standard error of 1.837 years. This specification indicates a longer cycle than the ten to twelve-year cycle observed from the 1930's until the 1980's.

With both cycles sharing a common frequency, it is possible to investigate the phase shifts between the cycles. The phase at time t for cycle i is represented by $\varphi_{it} = \tan^{-1}\left(\frac{\psi_{it}^*}{\psi_{it}}\right)$. Then if $\varphi_{jt} > \varphi_{it}$, y_{jt}leads y_{it} by $\frac{\varphi_{jt}-\varphi_{it}}{\lambda}$ time periods at time t. Generally, the feeder steer/corn price ratio leads cow herd. We do see, however, that during the decade of the 1990's that the two cyclical components are largely in antiphase. Although the phase shifts have a high degree of variability, the joint model with common frequency suggested that on average the feeder steer/corn price ratio cyclical component leads the cow herd size cyclical component by 5 periods. However, in subsequent estimation of the joint model with $\alpha\psi_{2t-s}$ in the state equation for cow herd, the best fit appears to be including the term $\frac{\alpha(\psi_{2,t-3} + \psi_{2,t-4})}{2}$.

Because of the counter cyclical pattern found in the late 20th Century, a final specification was investigated. This was to allow the coefficient on the feeder steer/corn price ratio cyclical component in the herd equation to vary over time according to $\left(\alpha_0 + \alpha_1 t^{\frac{1}{2}} + \alpha_2 t\right) \cdot \frac{\psi_{2,t-3} + \psi_{2,t-4}}{2}$. Estimation results for this model are reported in Table 4.

Table 4 Bi-variate First-order Stochastic Cycle Model

Parameter/ Coefficient	Estimated Value	Robust Std. Error	z-Value
DV_1	0.7233	0.0443	16.339
$\sigma_{1\kappa}=\sigma_{1\nu}$	0.2635	0.0347	7.6
$\lambda_1= \lambda_2$	0.1943	0.0247	7.869
β_1	-0.0681	0.0079	-8.605
ψ^*_{10}	1.12	1.828	0.613
y_{1t-4}	-0.0879	0.0444	-1.981
α_0	0.5685	0.164	3.466
α_1	-0.1582	0.0504	-3.139
α_2	0.0112	0.0038	2.941
DV_2	4.4908	0.7216	6.224
$\sigma_{2\kappa}=\sigma_{2\nu}$	5.4214	0.4202	12.903
β_2	0.5991	0.1844	3.249
ψ^*_{20}	19.9347	12.5686	1.586
y_{2t-4}	-0.3611	0.1317	-2.743
Log-likelihood	-259.88		

These joint results generate a cattle cycle of 16.17 years with an asymptotic standard deviation of 2.06 years. The mean effect of feeder steer/corn price ratio cyclical component on the cow herd is 0.072. The phase shift in terms of the number of semi-annual periods that the cyclical component of the feeder steer/corn price ratio leads the cow herd component is illustrated in

Figure 2. This phase shift is smoothed using a simple 3 period moving average. Note that

when the shift exceeds one-half the cycle length, one can interpret this as the series lagging the herd size by the cycle-length minus the phase shift. Since we infer that cow herd does not Granger cause the feeder steer/corn price ratio, we do not adjust the representation. In the figure, we also plot the total scaled (by 50) coefficient on the feeder steer/corn price ratio cyclical component on the cow herd. We see that the coefficient is smallest when the two cycles are most out of phase.

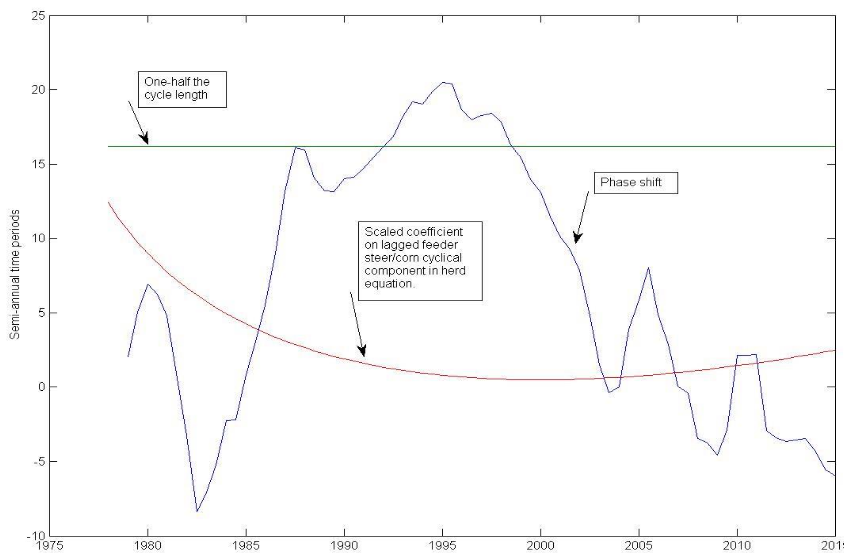

Figure 2 Phase Shift in Semi-Annual Periods

4. The Higher–Order Stochastic Cycle Model

a) Generalized Stochastic Cycles

Instead of the basic model in previous sections, which incorporates a first – order stochastic cycle, we consider applying a higher – order stochastic model to explore the periodic dynamics of the beef cow inventories. Periodic behavior can be more clearly defined by generalized cycles as they have more power concentrated near the spectral peak (Trimbur, 2005). Examples in Harvey and Trimbur (2003) showed smoother cycles in economic series can be extracted by generalized cyclical processes. Allowing for variation in the amplitude and phase over time as the first-order stochastic cycle does, the higher order cycles produce a more flexible description of periodic behavior in time series data. Additionally, the interpretation of parameters remains straightforward and as such the cyclical pattern can be studied directly. Extensions to multivariable models are also possible.

The unobserved component $\psi_t^{(m)}$ is defined as an m^{th}-*order* stochastic cycle, if

(8) $$\begin{bmatrix}\psi_t^{(1)}\\ \psi_t^{(1)*}\end{bmatrix} = \rho\begin{bmatrix}\cos(\lambda) & \sin(\lambda)\\ -\sin(\lambda) & \cos(\lambda)\end{bmatrix}\begin{bmatrix}\psi_{t-1}^{(1)}\\ \psi_{t-1}^{(1)*}\end{bmatrix} + \begin{bmatrix}\kappa_t\\ \kappa_t^*\end{bmatrix}, t = 1,2, \ldots T$$

(9) $$\begin{bmatrix}\psi_t^{(i)}\\ \psi_t^{(i)*}\end{bmatrix} = \rho\begin{bmatrix}cos(\lambda) & sin(\lambda)\\ -sin(\lambda) & cos(\lambda)\end{bmatrix}\begin{bmatrix}\psi_{t-1}^{(i)}\\ \psi_{t-1}^{(i)*}\end{bmatrix} + \begin{bmatrix}\psi_{t-1}^{(i-1)}\\ \psi_{t-1}^{(i-1)*}\end{bmatrix}, t = 1,2, \ldots T, i = 1,2,..m$$

where κ_t and κ_t^* are uncorrelated white-noise processes with zero mean and common variance σ_κ^2. ρ is the damping factor, which is bounded between 0 and 1. The cycle is stationary if $\rho < 1$. The stochastic nature of cycles comes from the disturbances $\begin{bmatrix}\kappa_t\\ \kappa_t^*\end{bmatrix}$. The higher order stochastic cycles are more flexible than the first order one because when order increases, the disturbances can have impact on cycles in different ways, thus resulting in different dynamic properties. Although cycles can be reduced to autoregressive moving-average (ARMA) form, they are more often represented in a state-space form, as this is the easiest way in terms of estimation calculation and offers more intuitive parameterization than the reduced form. Therefore, we put an m^{th}-*order* cycle in a state-space form, with the transition equation specified as

(10) $$\boldsymbol{\psi}_t = \boldsymbol{T}_m\boldsymbol{\psi}_{t-1} + \boldsymbol{c}_m \otimes \begin{bmatrix}\kappa_t\\ \kappa_t^*\end{bmatrix}$$

where $\boldsymbol{\psi}_t = [\psi_t^{(m)}, \psi_t^{(m)*}, \psi_t^{(m-1)}, \psi_t^{(m-1)*}, \ldots, \psi_t^{(1)}, \psi_t^{(1)*}]'$ is the state vector with 2*m* elements. The last element of the $m\times 1$ vector $\boldsymbol{c}_m$ is one, with zeros elsewhere. $\boldsymbol{T}_m$ is given by

(11) $$\boldsymbol{T}_m = \boldsymbol{I}_m \otimes \boldsymbol{T} + \boldsymbol{S}_m \otimes \boldsymbol{I}_2$$

where the transition matrix $\boldsymbol{T}$ is given by $\boldsymbol{T} = \rho \begin{bmatrix} \cos(\lambda) & \sin(\lambda) \\ -\sin(\lambda) & \cos(\lambda) \end{bmatrix}$, and $\boldsymbol{S}_m$ is a matrix with ones on the diagonal strip to the right of the main diagonal and zeros elsewhere. The variance – covariance matrix of the disturbance vector $\boldsymbol{c}_m \otimes \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix}$ is given by

$$(12) \quad VAR\left(\boldsymbol{c}_m \otimes \begin{bmatrix} \kappa_t \\ \kappa_t^* \end{bmatrix}\right) = \boldsymbol{c}_m \boldsymbol{c}'_m \otimes \begin{bmatrix} \sigma_\kappa^2 & 0 \\ 0 & \sigma_\kappa^2 \end{bmatrix}$$

b) Fitting Annual Beef Cow Inventories using Second-Order Stochastic Cycle Model

As mentioned earlier in Section 2, the beef cow numbers of January were collected directly from survey, while the numbers of July were derived from market information and a much smaller survey sample. Consequently, there is concern that the results from using semi-annual data may partially be an artifact of the reduced sample used to calculate mid-year inventories. With this in mind, we now focus on modeling annual data using the January inventories. Two series are analyzed in this section: the U.S. beef cow numbers (y_1) and feeder cattle – hay (U.S. average price) price ratios (y_2). For the semi-annual model the ratio of feeder calf to corn price is much more closely associated with beef cow inventories than the feeder calf to hay price ratio. For annual data, it is just the opposite. Both series are annual dated from 1972 to 2017. The new data set is different in two aspects versus the previous dataset: 1) a different price ratio is introduced, as hay is another important input price for feeder cattle since they are primarily fed on forages; 2) both series are annual and cover a longer time period, thus we believe a smoother cycle may be extracted from annual data.

Figure 3 plots the series of annual beef cow numbers and the feeder steer/hay price ratios from 1972 to 2017, both of which are trend adjusted and standardized. From the plot, we notice that the feeder steer/hay price ratio appears to have more cyclical behavior than cow numbers, and that counter-cyclical pattern exists between two series. Those findings are similar as shown in Figure 1.

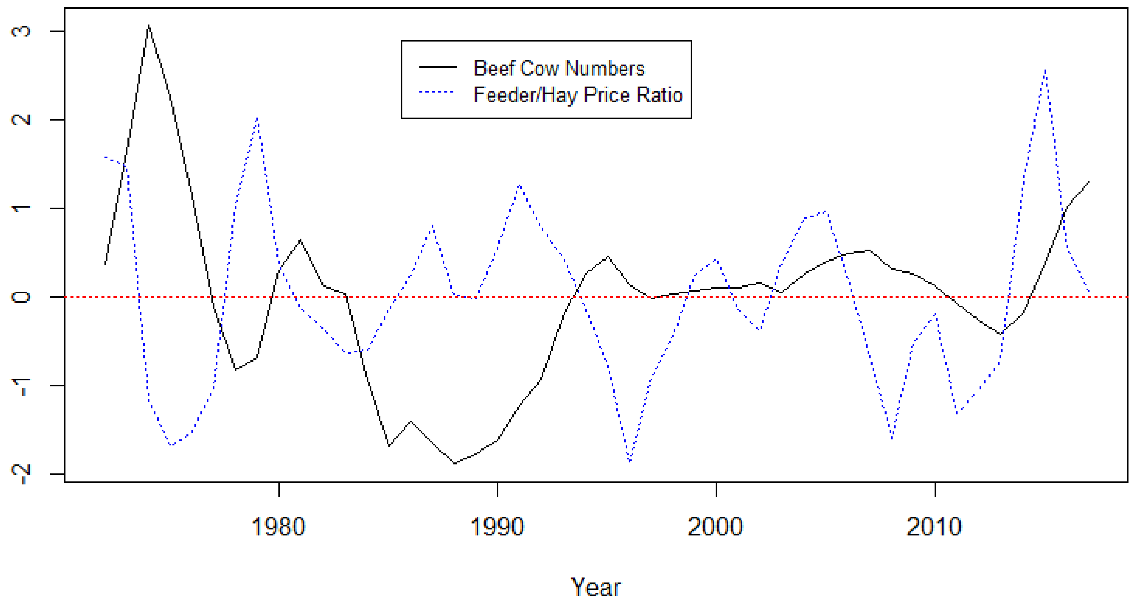

Figure 3 Trend Adjusted Beef Cow Numbers and Feeders Steer/Hay Price Ratio (Annual)

We then start analyzing each series with the univariate model with a second – order stochastic cycle component. The system is specified in equations (13) – (16).

(13) $$y_t = \mu_t + \psi_t^{(2)} + \varepsilon_t$$

(14) $$\mu_t = \beta_0 + \beta_1 t$$

(15) $$\begin{bmatrix} \psi_t^{(1)} \\ \psi_t^{(1)*} \end{bmatrix} = \rho \begin{bmatrix} cos(\lambda) & sin(\lambda) \\ -sin(\lambda) & cos(\lambda) \end{bmatrix} \begin{bmatrix} \psi_{t-1}^{(1)} \\ \psi_{t-1}^{(1)*} \end{bmatrix} + \begin{bmatrix} \kappa_t \\ \upsilon_t \end{bmatrix}$$

(16) $$\begin{bmatrix} \psi_t^{(2)} \\ \psi_t^{(2)*} \end{bmatrix} = \rho \begin{bmatrix} cos(\lambda) & sin(\lambda) \\ -sin(\lambda) & cos(\lambda) \end{bmatrix} \begin{bmatrix} \psi_{t-1}^{(2)} \\ \psi_{t-1}^{(2)*} \end{bmatrix} + \begin{bmatrix} \psi_{t-1}^{(1)} \\ \psi_{t-1}^{(1)*} \end{bmatrix}$$

where μ_t is the trend component, and $\psi_t^{(2)}$ is the 2^{nd} – *order* stochastic cycle component. All parameters and disturbances follow the same definition as in equations (1) – (4). Note that in contrast with the random walk with drift in Equation (2), μ_t in Equation (13) is now a trend component with a constant, since both series are tested to be trend stationary according to ADF test and KPSS test.

We can also write equations (13) – (16) in the state-space form, with the measurement equation and transition equation specified as in Equation (17) and (18), respectively

(17) $y_t = \boldsymbol{Z}_t' \boldsymbol{\alpha}_t + \boldsymbol{X}_t \boldsymbol{\beta} + \varepsilon_t$ (Measurement equation)

(18) $\boldsymbol{\alpha}_t = \boldsymbol{T}_2 \boldsymbol{\alpha}_{t-1} + \boldsymbol{c}_2 \otimes \begin{bmatrix} \kappa_t \\ \upsilon_t \end{bmatrix}$ (Transition equation)

where $\mathbf{Z}_{\mathrm{t}} = [1,0,0,0]'$, $\boldsymbol{\alpha}_t = [\psi_t^{(2)}, \psi_t^{(2)*}, \psi_t^{(1)}, \psi_t^{(1)*}]'$, $\boldsymbol{X}_t = [\mathbf{j}, \mathbf{t}]$, $\mathbf{j} = [1, \ldots, 1]'$ and $\mathbf{t} = [1, 2, \ldots, \mathrm{T}]'$; $\boldsymbol{\beta} = [\beta_0, \beta_1]'$; ε_t is assumed to be iid normally distributed with mean zero and constant variance σ_ε^2.

In the transition equation, $\boldsymbol{T}_2 = \begin{bmatrix} \rho\cos(\lambda) & \rho\sin(\lambda) & 1 & 0 \\ -\rho\sin(\lambda) & \rho\cos(\lambda) & 0 & 1 \\ 0 & 0 & \rho\cos(\lambda) & \rho\sin(\lambda) \\ 0 & 0 & -\rho\sin(\lambda) & \rho\cos(\lambda) \end{bmatrix}$, and $c_2 = [0,1]'$.

The system involves ten parameters: β_0, β_1, ρ, λ, σ_ε, σ_κ, σ_ν, and the initial conditions ψ_0, ψ_0^*, μ_0. Restriction $\sigma_\kappa = \sigma_\nu$ is imposed for two series, while the additional restriction $\sigma_\varepsilon = 0$ is applied to the cow herd size series. The system is estimated by maximum likelihood, and the optimization is achieved by Kalman filter algorithm. Additionally, we also estimated a *first – order* stochastic cycle model for each series, with the cyclical component $\psi_t^{(2)}$ in Equation (13) replaced by the basic (first-order cycle) ψ_{t} as defined in Equation (1). Estimation results for beef cow numbers and feeder steer/hay price ratios are shown in Table 5 and Table 6, respectively. For each series, the estimated coefficients are quite similar between the 1^{st} – and 2^{nd} – order cycle models, with the exception of the estimated initial conditions ψ_0, ψ_0^*, and the estimated variances when modeling the price ratio series. Moreover, for both series, the second – order stochastic cycle model has better fit in terms of log-likelihood vs. the first – order cycle model.

Therefore, the estimated coefficients illustrated below only refers to those obtained from the 2nd – order stochastic cycle model, unless otherwise noted.

For the cow herd series, we find a downward trend indicated by $\hat{\beta}_1 = -0.19$. The damping factor $\hat{\rho} < 1$ suggests the cow herd series is stationary after the trend is controlled, which is consistent with the stationarity test results. The estimate of λ implies a cycle period of $\frac{2\pi}{\hat{\lambda}} = 15.8$ years, with an asymptotic 95% confidence interval of 9.9 to 21.5 years calculated by the Delta method.

Comparatively, the feeder steer/hay price ratio is found to have an upward trend ($\hat{\beta}_1 = 0.03$) and trend-stationary as suggested by $\hat{\rho} = 0.68$<1. The estimate of λ implies a cycle period of $\frac{2\pi}{\hat{\lambda}} = 7.7$ years, with an asymptotic 95% confidence interval of 6.3 to 9.1 years.

Table 5 Univariate Model – Cow Herd Size

Parameter/ Coefficient	Estimated Value	Robust Std. Error	z-Value	Estimated Value	Robust Std. Error	z-Value
	1st – order stochastic cycle			2nd – order stochastic cycle		
β_0	38.1809	0.8521	44.808	38.6445	1.3083	29.538
β_1	-0.1766	0.0263	-6.725	-0.1916	0.0393	-4.879
λ	0.4078	0.0564	7.225	0.3987	0.075	5.313
ρ	0.8051	0.0571	14.111	0.6166	0.0766	8.048
$\sigma_\kappa = \sigma_\nu$	0.6725	0.0994	6.763	0.5731	0.0831	6.897
ψ_0	-2.4438	1.5602	-1.566	2.0885	1.5332	1.362
ψ_0^*	14.826	4.0488	3.662	5.8175	1.8522	3.141
Log-likelihood	-51.0081			-46.2891		

Table 6 Univariate Model – Feeder Steer/Hay Price Ratio

Parameter/ Coefficient	Estimated Value	Robust Std. Error	z-Value	Estimated Value	Robust Std. Error	z-Value
	1st – order stochastic cycle			2nd – order stochastic cycle		
β_0	9.844	0.6179	15.932	10.1881	0.5381	18.935
β_1	0.0381	0.0258	1.476	0.0268	0.0225	1.187
λ	0.8171	0.1077	7.586	0.8158	0.0751	10.864
ρ	0.8393	0.1088	7.716	0.6770	0.0695	9.736
$\sigma_\kappa = \sigma_\nu$	1.1672	0.4242	2.751	0.6217	0.1973	3.151
σ_ε	0.3755	1.0023	0.375	0.7685	0.1525	5.040
ψ_0	3.3024	4.0022	0.825	3.8265	0.8026	4.768
ψ_0^*	3.2128	3.6591	0.878	-1.0547	1.1894	-0.887
Log-likelihood	-83.8315			-81.4284		

To gain more precise parameter estimates with pooled information, we estimated a bi-variate model where the cyclical components of two series are modeled jointly. For the cow herd size, all the estimated coefficients are quite close to those obtained by the univariate second – stochastic cycle model, while the coefficients on the feeder steer – hay price ratio are found to be slightly different than those in the univariate second – order cycle model. Moreover, most of the estimated coefficients have smaller standard errors than in the univariate second – order cycle model, suggesting improved model fit. The frequency associated with cow inventories λ_1 is estimated to be 0.36, implying a cow cycle period of $\frac{2\pi}{\hat{\lambda}} = 15.7$ years with an associated standard error of 3.45 years. An asymptotic 95% confidence interval of 9.1 to 22.7 years is calculated by Delta method. The estimated 15.7-year cycle period is very close to the 16.1-year cycle estimated by the bi-variate first – order stochastic cycle using semi-annual data. Both approaches confirm a significant lengthening cow cycle in contrast with the 10-year cycle from literature in early 2000s. To investigate the interrelationships between the two stochastic cycles, we augment the state equation for the cow numbers by adding the term $\psi_{2,t-s}$. A number of lags were investigated to see if they affect cow numbers and also to see if an asymmetric response was operating. Finally, we arrived at $\psi_{2,t-1}$,which is coded as the one year lag of the fitted feeder/hay ratio cycle component if the fitted value is positive, otherwise $\psi_{2,t-1} = 0$. We found only this specification gave a highly significant parameter estimate. The estimated coefficient on $\psi_{2,t-1}$ implies a strange asymmetry in that the one-year lag of the feeder/hay price ratio cycle ($\psi_{2,t-1}$) only affects herd size (y_1) when the ratio is at the period when the cycle is above zero ($\psi_{2,t-1} > 0$). The implication of such asymmetry could be interpreted as only when the feeder/hay price ratio cycle is at positions above historical mean (or expectation) would it lead to an increase in cow-herd sizes, if we think of the feeder/hay price ratio cycle as a mean reverting process. On the opposite, when the feeder/hay price ratio is below expectation, the inventories would remain at the same level in cow-calf operations. There could be an economic reason in that reducing herd size is usually costly, so cattle ranchers maintain herds when profitability is limited and tend to expand when the economic environment improves. Increasing herd size is not as costly as ranchers can retain some of their heifers.

The residual serial correlation of the joint model is checked by Ljung-Box Q-test and p-values of 0.583 and 0.403 over 12 lags for residuals for y_1 and y_2 series, respectively, suggesting no severe serial correlations exist.

Table 7 Bi-variate Second-order Stochastic Cycle Model

Parameter/ Coefficient	Estimated Value	Robust Std. Error	z-Value
$\beta_{1,0}$	38.6536	0.9673	39.960
$\beta_{1,1}$	-0.2016	0.0283	-7.113
λ_1	0.3962	0.0862	4.596
ρ_1	0.6645	0.0570	11.655
$\sigma_{1\kappa} = \sigma_{1\nu}$	0.4350	0.0784	5.547
$\psi_{1,0}$	1.9839	1.0874	1.825
$\psi^*_{1,0}$	3.8479	1.3865	2.775
$\beta_{2,0}$	9.9667	0.4692	21.243
$\beta_{2,1}$	0.0332	0.0193	1.726
λ_2	0.8453	0.0544	15.542
ρ_2	0.7258	0.0751	9.661
$\sigma_{2\kappa} = \sigma_{2\nu}$	0.5051	0.1699	2.972
$\sigma_{2\varepsilon}$	0.8510	0.1282	6.638
$\psi_{2,0}$	1.2899	0.9288	1.389
$\psi^*_{2,0}$	1.4882	0.7097	2.097
$\psi_{2,t-1}$	0.4015	0.0947	4.240
Log-likelihood	-120.3573		

5. Summary and Conclusions

In this chapter, we began our analysis on the dynamics of beef cow numbers with a basic (first-order) stochastic cycle model utilizing the semi-annual data of beef cow inventories and feeder/corn price ratios from January 1978 to July 2015. Results from the joint first-order stochastic model imply a cattle cycle of 16.17 years with an asymptotic standard deviation of 2.06 years. Since a few drawbacks were identified in the semi-annual data and to extract a smoother cycle of beef cow inventories, we applied a second-order stochastic cycle model with annual series of beef cow numbers and feeder/hay price ratios, which is believed to be more closely associated with annual cow numbers than the previously used feeder/corn price ratios. In addition, the first-order stochastic cycle model is also applied to each series, and as expected, the second-order stochastic cycle model always fits the data better. Similarly, the joint second-order cycle model results imply a cattle cycle of 15.7 years with an associated standard error of 3.45 years. Therefore, both approaches showed a lengthening cattle cycle of over 15 years than the previous 10 to 12 year cycles investigated by literature in early 2000s. The larger standard error associated with the cycle estimated by the second-order cycle fitting annual data can be partly attributed to there being fewer observations than the semi-annual data. It also may be caused by the interpolation algorithm applied to the semi-annual cow inventories, which leads to a smoother series than annual series. Moreover, an asymmetric impact of the first lag of the feeder/hay price ratio component on the cow herd sizes is identified. Specifically, the first lag of the feeder/hay price ratio component only has impact on cow numbers when it is positive. This could be possibly explained by the fact that for cattle ranchers, reducing herd size is usually more costly than increasing herd size, as they can retain some of their heifers. Thus ranchers would rather maintain herds when profitability is limited and tend to expand when the economic environment improves.

Although the identification of commodity price cycles can be viewed as purely a statistical exercise, the presence of cycles has important implications. Beveridge and Nelson

(1981) have pointed out that the observation of cyclical components in economic time series "has played an important role in shaping our thinking about economic phenomena" (p151.) In this case, we observe a significant lengthening of the cattle cycle. Typically cycles become longer before they disappear. Whereas the popular press has already buried the cattle cycle (Speer, 2014) given the observed patterns in herd size since the 1990's, the stochastic cycle model shows its continued, albeit altered, existence.

This leads to speculation as to why in recent decades the cycle is significantly longer than the ten to twelve year cycle observed over most of the 20th Century. Since 2000 there have been a number of events which have been linked to a lengthening cattle cycle—specifically due to a long trend of decreasing number of beef cows. There were a number of droughts in major cow-calf producing areas from 2000 to 2008 and again in the southern plains from 2010 to 2013 (Petry, 2015). Higher row crop prices and the consequent expansion of crop production may also have led to a reduction in cow-calf operations. According to the 2012 Census of Agriculture, there was a decline of almost 175,000 cow calf operations in the previous 20 years with a bulk of these operations having less than 50 cows.

The significant lengthening cycle in beef cow supply suggests rational expectation hypothesis might not hold in the cattle industry. Under a fully rational expectation theory, fully rational forward-looking ranchers anticipate future cattle cycles, which were known to be 10-years, and take actions to mitigate them. And their actions would endogenously generate or realize another 10-year cycle in future, if fully rational expectation theory holds. There are also quite a few studies that put in question the appropriateness of full rational expectations in the cattle industry (Nerlove and Fornari, 1998; Baak, 1999; Chavas 2000) as most cattle market participants are found to be not fully rational (eg. quasi-rational or boundedly rational). Howerer, Aadland (2002) showed that individual optimizing behaviour endogenously generated approximate 10-year cycles in cattle supply even under a less restricted assumption that ranchers are only boundedly rational (i.e. ranchers have limited access to future information and form expectations of future prices based on only past or current information).

While there is still a debate on whether rational expectation theory holds in the cattle industry, exogenous shocks hitting the cattle industry could partly explain the lengthening cycle in beef cow supply. As noted previously, cattle feeding has undergone a major transformation since the 1960's. The advent of large, commercial feedlots with some being owned by meatpackers and others by more diversified firms suggests that conventional measures of feedlot returns may not reflect the rents of these operations. In 2005, the four largest processors of steers and heifers accounted for almost 80 percent of the market (MacDonald and McBride, 2009). It has also been noted that "Contractual relationships are becoming more complicated as backgrounders or cow-calf operations enter into joint ownership of cattle with feedlots or processors." (MacDonald and McBride, 2009).

While our bivariate stochastic cycle model cannot identify the precise causes of a lengthening cattle cycle, its value lies in showing that both the cow herd and the feeder steer/corn price ratio follow a stochastic cycle of essentially the same frequency, but with considerably different phases. It will be a matter of time to determine if the cycle continues to lengthen or if it reverts to a traditional cycle length in the 10- to 12-year range.

Under rational expectations theory, fully rational ranchers would anticipate the 10-year cycle and take actions to mitigate them, causing future cyclical fluctuation to be significantly dampened due to factors such as macroeconomic shocks, climate shocks, and input price shocks.

CHAPTER 2

DYNAMICALLY CHANGING CATTLE MARKET LINKAGES WITH SUPPLY SIDE-CONTROLLED TRANSITIONS

1. Introduction

Cattle as a perishable and bulky livestock is costly to transport, thus easily leading to segmented regional cattle markets. Under the assumption of a competitive market structure with a homogenous commodity and no trade barriers, price differences between any two regions that trade with each other will just equal transfer costs. This principle is usually referred to as the Law of One Price (LOP) in a spatial dimension. Geographical price relationships can be analyzed using spatial price equilibrium models (Tomek and Kaiser 2014). A set of prices can be obtained from the optimum that is determined by the model, given the supply and demand conditions within each region. The Law of One Price has been the basis for numerous tests of market efficiency and market integration (e.g., Ravallion 1986; Goodwin and Schroeder 1990, 1991; Barrett and Li 2002; Negassa and Myers 2007). Markets that are not integrated could reflect inadequate market information, poor marketing decisions, or potential trade barriers. The functioning of cattle markets is important as cattle are typically the highest total-value agricultural commodity produced in the U.S., running slightly ahead of corn. Cointegration tests can provide a suitable framework in which to consider long-run price relationships among regional cattle markets.

Several researchers have investigated market integration in the U.S. cattle market. Bailey and Brorsen (1985) investigated the dynamics of weekly slaughter steer prices from January

1978 through June 1983 in four cattle feeding regions using a multivariate autoregressive frame work. Cattle prices in the Texas Panhandle market led cattle prices in Utah-Eastern Nevada-Southern Idaho, Colorado-Kansas, and Omaha, Nebraska, but Omaha prices fed back to Texas. Schroeder and Goodwin (1990) examined 11 direct and terminal trade cattle markets from 1976 through 1987. They found cattle markets with larger volumes fully reacted to price changes at the other major cattle markets, usually within one or two weeks. However, small-volume markets, located on the fringe of major feeding regions, took two to three weeks to fully respond. The empirical applications by Goodwin and Schroeder (1991) suggested that cointegration was somewhat limited, with about half of the tests indicating integrated markets. Schroeder (1997) found that the degree of cointegration is affected by distances between cattle markets, procurement methods and size and ownership of packing plants. Pendell and Schroeder (2006) found that regional cattle markets have been, and remain, highly integrated after implementation of mandatory price reporting. Our analysis extends the work of earlier studies in evaluating cattle price cointegration by using a Smooth Transition Autoregression model, which allows the degree of market integration to change over time in response to variation in an outside economic indicator.

Time-Varying Smooth Transition Autoregressions (TV–STARs) have been suggested to address nonlinearities induced by unobservable transactions cost. Goodwin et al. (2010) found markets with nonlinearities and structural changes; results also suggest the existence of price parity relationships. Hood and Dorfman (2015) constructed an ECON-STAR model to capture the relationship between housing starts and southern U.S. regional pine sawtimber stumpage prices. This model was new, with the novelty being that an economic indicator is included in the model to control the transitions between unlinked and integrated regional markets. Because

Bekkerman, Goodwin, and Piggott (2013) show that generalizing beyond simple cointegration models is important for accurate model of price dynamics in spatially-linked markets, applying an ECON-STAR model to regional U.S. cattle markets seems very appropriate.

In this paper, we are interested in whether large cattle inventories encourage efficient trading. Thus, as the volume of cattle inventories changes, we are curious about the changes in the market linkages of the numerous, regional markets. To develop this topic, we are going to test whether the level of inventory has an impact on the cointegration of cattle prices in U.S. cattle markets by applying and modifying the work of Hood and Dorfman (2015) which introduced the generalized smooth transition autoregressive (STAR) model with an outside economic indicator. Market integration occurs when prices among different locations or related goods follow similar patterns in long run. Empirically, a stationary price differential between two markets is the measure of market integration. The ECON-STAR model splits the evolution of price differences in two locations into two parts: an AR process (no market integration) and a mean-reverting process (market integration). The advantage of this model is that it allows for the possibility of gradual adjustments in the relative importance of the two parts, thus testing price linkages and allowing us to see how market dynamics change over time in response to variation in the embedded exogeneous economic indicator.

This paper makes three key contributions. First, by using adjusted inventory as the transition variable, the empirical results show how important excess regional supply in the market is for maintaining market integration. The analysis provides economists and policymakers with information regarding the true driving force of cattle market linkages. Second, while the cattle industry and cattle markets have undergone considerable structural change, there is a limited number of published and updated works testing spatial cattle price cointegration. Our analysis provides a more current assessment of spatial cattle market integration than the literature to date and covers a longer time span of cattle market data from 1950 to 2010. Third, the transition function in the ECON-STAR model is modified to bring more flexibility. We leverage the cumulative distribution function (CDF) of the standard normal distribution in the model, which eliminates the "minimum value" problem in the previous literature. In the original ECON-STAR model, the transition variable was guaranteed to reach zero at least once when the exogenous indicator's level reaches its minimum value, thus making a pair of regions unlink at least once even if they never did in fact. The natural features of the CDF of the standard normal distribution such as positivity, monotonicity, and continuity give the model higher flexibility and a better description of how markets link and unlink over time.

This final contribution is important for expanding the usefulness of the ECON-STAR model. Hood and Dorfman (2015) wanted a model for sawtimber where the vast swings in demand caused by the boom and bust cycles of home building caused markets to link and unlink. Yet few products experience such large swings in demand. Rather, particularly in agricultural and natural resource markets, demand tends to be relatively constant while supply shocks are a much more common source of disequilibrium. Thus, the application here which uses a supply-side variable to control the transition, if successful, would be applicable to a much wider array of commodity markets.

2. Data Description

The annual price series for more than 500 pound feeder cattle and levels of inventories (measured in head) including calves were assembled for 29 states (Arizona, Arkansas, California, Colorado, Florida, Georgia, Idaho, Illinois, Iowa, Kansas, Kentucky, Louisiana, Michigan, Minnesota, Missouri, Montana, Nebraska, New Mexico, North Dakota, Ohio, Oklahoma, Oregon, Pennsylvania, South Dakota, Tennessee, Texas, Virginia, Wisconsin, and Wyoming) over the period from 1950 through 2010, yielding a total of 61 observations per state. Figure 4 shows the data coverage of our study where dark areas indicate that data are not available for that state. The data were collected from the National Agricultural Statistics Service (NASS) of United States Department of Agriculture (USDA).

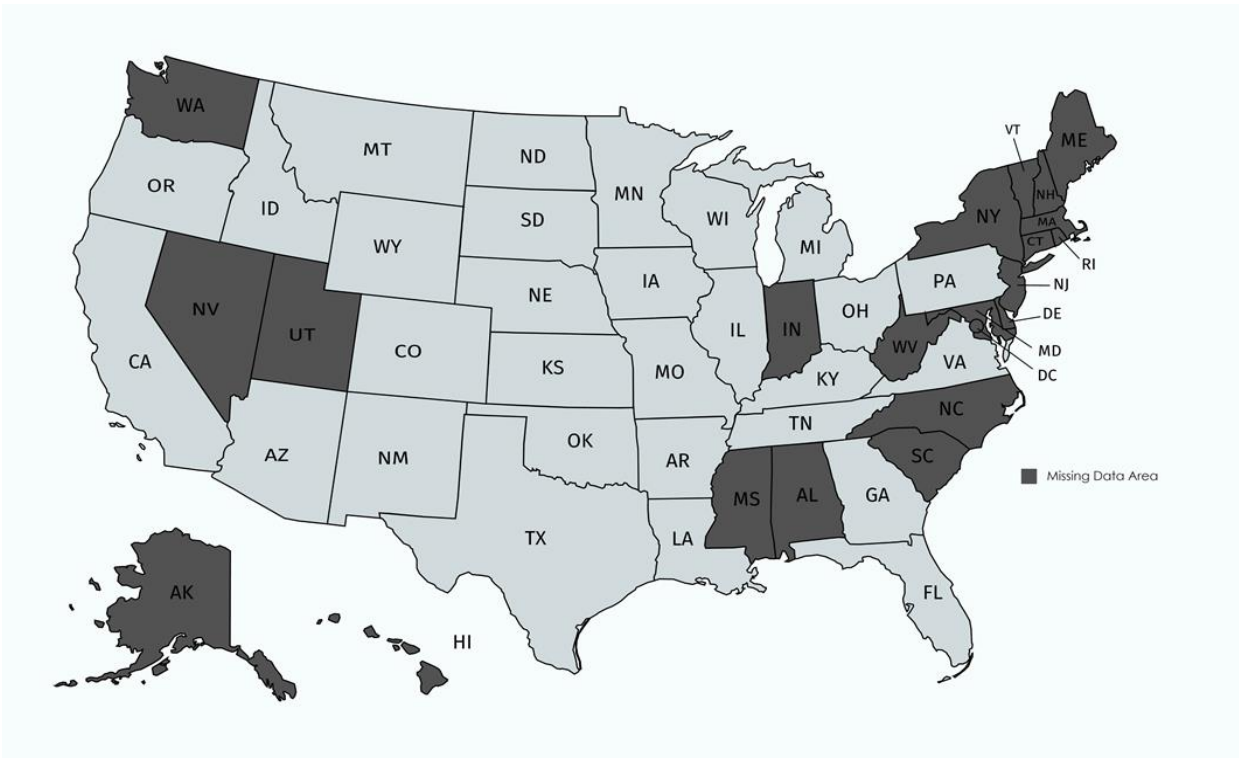

Figure 4 Data Coverage Map

The number of slaughtered cattle was chosen as the indicator for cattle demand because slaughtered cattle constitute over 90 percent of the total disappearance of cattle apart from deaths and exports. The data were collected from USDA NASS.

There are certain limitations regarding the data as the annual prices received for feeder cattle 500 lbs or greater are highly-aggregated. Monthly cattle prices by state for a specific weight range would be more ideal. We use annual data because USDA releases cattle inventories by state only on an annual basis and all the series applied in the model must have the same frequency. Moreover, the adequate number of annual observations, 61 observations for each state, provides essential variations to explore the dynamics in the market linkage pattern over time. Although cattle prices vary with weight range, which can be affected by factors such as drought conditions, forage prices, and grain feeding prices in different locations, the prices for cattle with an aggregated weight range of 500 lbs or greater is considered acceptable because we compare prices between two contiguous states with assumed similar characteristics. By doing this, factors mentioned above should be controlled to an acceptable degree.

Figure *5* illustrates the U.S. annual prices of cattle over 500 lbs in $/cwt and the U.S. annual level of inventories of cattle (including calves) from 1955 to 2010, showing the overall long-term history of the U.S. cattle market. As cattle prices climb over time, the level of cattle inventories expanded steadily beginning in the 1950s, reached its peak in 1975, and underwent a noticeable decline afterwards. We want to capitalize on the relationship between the level of cattle inventories, which is used as the economic indicator to study market linkages in this paper, and prices of cattle.

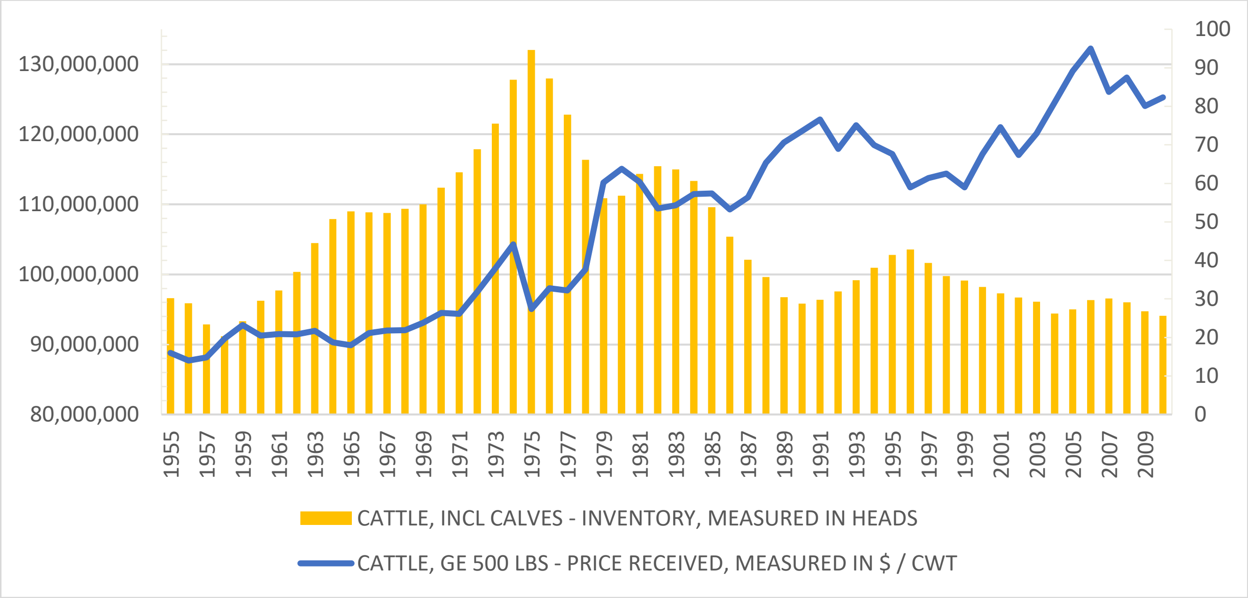

Figure 5 Annual Cattle Prices \$/Cwt vs Cattle Inventories, 1950 – 2010.

We standardized the series of national cattle inventory and national cattle disappearance by subtracting the mean and dividing the difference by the standard deviation to make these two series comparable.

Figure 6 shows the standardized annual number of the U.S. slaughtered cattle and the standardized annual level of the U.S. inventories of cattle (including calves) from 1955 to 2010. As an indicator of the demand for live cattle, the number of slaughtered cattle exhibit nearly the same trend as cattle inventories which can be considered as the supply of live cattle.

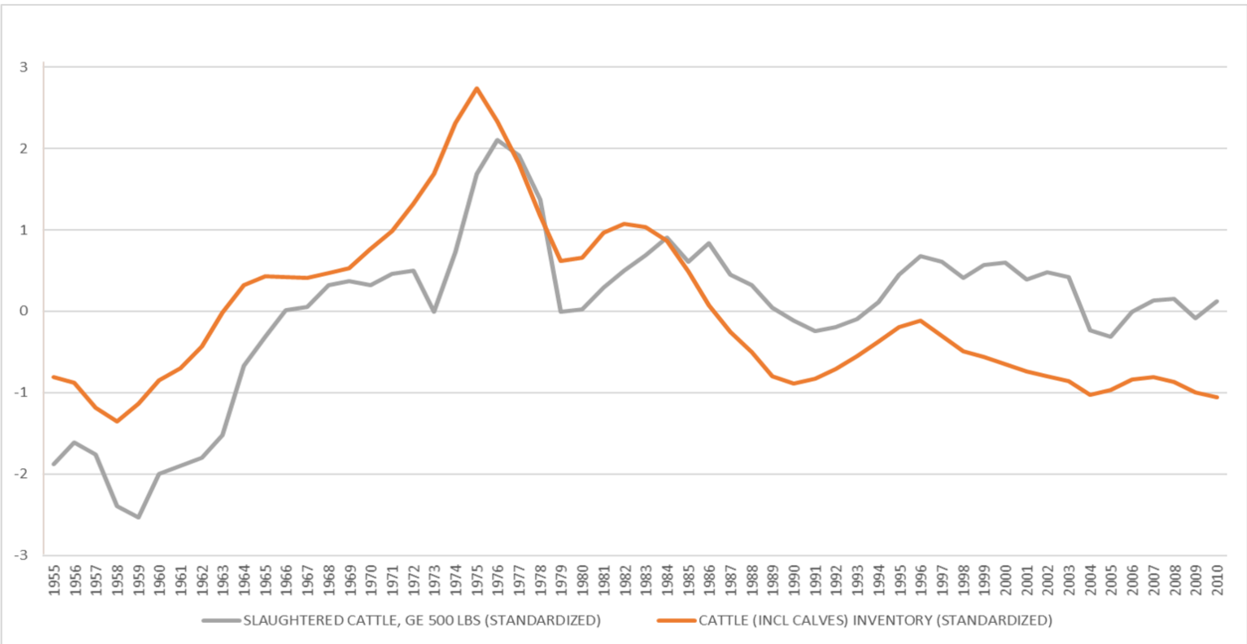

Figure 6 Standardized Annual Cattle Inventories vs Standardized Cattle Disappearance, 1955 – 2010.

3. Econometric Methodology

c) The Basic Model

Let $y_t = \ln(\frac{p_{it}}{p_{jt}})$ for some market *i* and *j*. We specify a linear qth–order autoregressive model for the price pair as

$$(1)\ \Delta y_t = \phi_0 + \boldsymbol{\phi}'\ \mathbf{x_t} + \theta y_{t-1} + \varepsilon_t$$

where $\boldsymbol{\phi} = (\phi_1, \dots, \phi_{q-1})'$, $\mathbf{x_t} = (\Delta y_{t-1}, \dots, \Delta y_{t-q+1})'$, ε_t is a mean-zero i.i.d. error term with finite variance. The lag length *q* will be chosen by using a model selection criterion such as Akaike's Information Criterion (AIC).

d) The STAR Model

In the basic STAR modelling framework used to investigate the LOP, the linear autoregression in the previous equation is typically modified as follows

$$(2)\ \Delta y_t = \widetilde{\boldsymbol{\phi}}_{\mathbf{1}}'\ \tilde{\mathbf{x}}_{\mathbf{t}}[1 - G(s_t;\gamma,c)] + \widetilde{\boldsymbol{\phi}}_{\mathbf{2}}'\ \tilde{\mathbf{x}}_{\mathbf{t}} G(s_t;\gamma,c) + \varepsilon_t$$

where $\tilde{\mathbf{x}}_{\mathbf{t}} = (1, x_t, y_{t-1})'$, $\widetilde{\boldsymbol{\Phi}}_{\mathbf{1}} = (0, \phi_{11}, 0)'$, $\widetilde{\boldsymbol{\Phi}}_{\mathbf{2}} = (\phi_{20}, \phi_{21}, \theta_{22})'$, and $\theta_{22} < 0$ is required; c can either be a scalar or a vector; s_t is the transition variable; $G(s_t;\gamma,c)$ is the transition function that varies smoothly between zero and one, in response to changes in s_t. The parameter γ, which is required to be positive, controls the speed–of–adjustment and determines how responsive *G* is to changes in *s*, and c is the location parameter(s). The values of γ and c determine the properties of transition function. As for the transition variable, s_t, it can be a function of nearly any observed variable. For example, Killian and Taylor (2003), in their investigation of the behavior of real exchange rates based on fundamentals of purchasing power parity (PPP), suggest using

$$(3)\ s_t = (\frac{1}{D_{max}}) \sum_{d=1}^{D_{max}} y_{t-d}\ ,$$

where D_{max} is a pre-specified lag limit. The specification in Equation (3) is also consistent with the notion that when the relative prices deviate far enough from some moving average, profit opportunities will occur.

In addition to the specification in Equation (3), a number of candidates have been proposed for the transition function G(•) (Goodwin, Holt, and Prestemon, 2011). The most commonly used specification of G(•) in market integration analysis is the exponential or ESTAR model. (see, e.g., Fan and Wei 2006; Kilian and Taylor 2003; Paya and Peel 2004; Taylor, Peel, and Sarno 2001). The ESTAR model expresses the transition function as

(4) $\mathrm{G}(s_t;\ \gamma, c) = 1 - \exp[-\gamma(s_t - c)^2]$,

where c is the location parameter and γ is the speed-of-adjustment parameter, and $\gamma > 0$ is required. This form of transition function is the basis for the ECON-STAR model we will employ. The ECON-STAR model proposed by Hood and Dorfman (2015) uses a transition function given by

(5) $\mathrm{G}(s_t;\ \gamma, c) = 1 - \exp\left\{-\gamma\left[\left(\frac{s_t - c}{\sigma_s}\right)\left(\frac{v_t - d}{\sigma_v}\right)\right]\right\}$,

where s_t and v_t are transition variables for two neighbouring markets, $s_t - c > 0$ and $v_t - c > 0$ are required, c and d are the minimum value of s_t and v_t.

The ECON-STAR model we propose here takes the following form based on the ECON-STAR model by Hood and Dorfman (2015):

(6) $\Delta y_t = \boldsymbol{\psi}_1^{'}\ \tilde{\mathbf{x}}_t[1 - G(s_t;\gamma, c)] + \boldsymbol{\psi}_2^{'}\ \tilde{\mathbf{x}}_t G(s_t;\gamma, c) + \varepsilon_t$,

where $\tilde{\mathbf{x}}_t = (1, x_t, y_{t-1})'$, $\boldsymbol{\psi}_1^{'}\ = (0, \phi_{11}, 0)$, $\boldsymbol{\psi}_2^{'}\ = (\phi_{20}, \phi_{21}, \theta_{22})$, and where $\theta_{22} < 0$ is required. Thus, when the transition function G = 1, ψ_2 are the controlling coefficients and markets will be integrated. We propose and use a modified transition function to accommodate transition variables that represent the level of cattle inventories, replacing the demand-side variable of Hood and Dorfman (2015) with a supply-side controlled transition.

In our model, we use the adjusted level of cattle inventory defined as the annual level of cattle inventories over the corresponding annual level of the disappearance of cattle, which is treated as the indicator of demand for live cattle. This variable thus measures supply relative to demand in each of the observed time periods. Define the transition variable s_t as

(7) $s_{it} = \frac{I_{it}}{D_t},\ s_{jt} = \frac{I_{jt}}{D_t}$.

Here I_{it} and I_{jt} denote the total cattle (including calves) inventories in state *i* and state *j*, respectively at time *t*, D_t is the number of slaughtered cattle in the U.S. (annual disappearance). The resulting transition function is given by:

(8) $G(s_{it}, s_{jt};\ \gamma, \mu) = 1 - \exp[-\gamma * \Phi\left(\frac{s_{it}-\mu_i}{\sigma_i}\right)\Phi\left(\frac{s_{jt}-\mu_j}{\sigma_j}\right)]$.

In equation (8), μ_i and μ_j are the mean values of the respective transition variables, s_{it} and s_{jt}, $s_t - \mu$ is normalized by σ to make the speed-of-adjustment parameter, γ, unit free, and $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution. The reason that we apply the CDF of a standard normal is that it exhibits nice properties for our purposes: it has flatter tails when the value goes to extremes, has almost linear movement for values within two standard deviations about zero, and satisfies the positivity requirement that keeps the transition function bounded between 0 and 1. This property gives the model higher flexibility and a better ability to track how markets link and unlink over time. In the original ECON-STAR model of Hood and Dorfman (2015), the transition variable must go to zero at least once when its value reaches the minimum value, thus making a pair of states unlink at least once. However, by inserting the transition variable into a CDF, this problem is avoided since a CDF always returns a positive value.

The natural economic interpretation of the transition function is the same as in other variants of STAR models applied to market integration testing: values equal to one indicate linked markets and values equal to zero indicate unlinked markets. Interpretation of values between the two extremes is more subjective, especially for intermediate values within this range. However, while interpretation of intermediate values is somewhat subjective, one could think of STAR models as switching regime models with infinite states. The transition function, $G(s_t;\gamma,c)$, is strictly increasing with s_t, the ratio of state-level supply to national-level disappearance, which indicates the degree of local excess supply. Therefore, $1-G(s_t;\gamma,c)$ is strictly decreasing with s_t. We assign $1-G(s_t;\gamma,c)$ to the "unlinked" component, $\boldsymbol{\psi}_1^{'}\ \tilde{\mathbf{x}}_t$, where the parameters are restricted to $\boldsymbol{\psi}_1^{'}\ =(0,\phi_{11},0)$, because when the supply cannot meet a higher demand in general, it is more likely cattle are traded within rather than between regions. Thus, prices at different regions would be less likely to be cointegrated. On the other hand, cattle are more actively traded between regions when excess supply exists. Therefore, $G(s_t;\gamma,c)$ is assigned to the "linked" component. The model is able to describe the reality that there is always trade between regions since $G(s_t;\gamma,c)$ never reaches zero, but whether prices in different regions are cointegrated depends on the trading volume.

4. Estimation Results

a) Final Model Results

We evaluated 55 state-pairs using the above described model. Price pairs were selected to include all states that are contiguous to each other. The sample size is large enough to draw inference about market linkages among all regions evaluated. Results indicate that strong growth in the level of cattle inventory can cause numerous states to link together and function as one unified market.

The lag length was set to p=3 for all models based upon both AIC and BIC criteria. The speed-of-adjustment parameter, γ, which enters the equation non-linearly, is estimated to maximize the predictive strength of the final model. To estimate this parameter, we scanned over a range of γ values. For each fixed value of γ, the remaining parameters were estimated by maximum likelihood. The γ value that resulted in the highest likelihood function value was chosen as the estimate. This is equivalent to joint maximum likelihood of all the parameters.[1]

A maximum and minimum value constraint is imposed to restrict the speed-of adjustment parameter from going to zero or ∞. The minimum value of γ is set to 0.05, and the maximum value is set to 300. The smaller the parameter value, the slower the two regional cattle markets link and unlink, and the larger the parameter value, the quicker the two regions adjust between linked and unlinked.

b) Market Linkages

We highlight four time periods (Figure 7 and Figure 8) to show how cattle market linkages changed throughout the sample period: 1959, 1966, 1986, and 2005[2]. We used $G(s_t) \geq 0.9$ as the value required to signify market linkage, which sets the bar fairly high. When two or more states are linked, we define these states as a distinct regional market, which is a higher level market than state market. Results indicate that in 1959, when the adjusted level of inventories reached a historic high, there were two distinct regional markets: 1) MT, ID, WY, ND, SD and MN; and 2) CO, NM, NE, KS, OK, TX, IA, MO, AR, WI, IL, MI, OH, KY, TN, GA, FL, PA and VA. In 1966, three regional markets are observed: 1) MT, ID, WY, ND, SD and MN; 2) NE, KS, TX, IA, MO, AR, WI, IL, MI, OH, KY, TN, GA, FL and PA; and 3) CO, NM and OK. With the decrease in available supply, we notice that Colorado, New Mexico and Oklahoma have separated from their earlier, larger regional market. As Figure 7 shows, the size of the big central

[1] In our case, the speed-of-adjustment parameter value that maximizes the likelihood function also maximizes the R-squared model statistic, so we used this statistic to estimate the speed-of-adjustment parameter.

[2] Full results for all estimated pairs are available from the authors on request.

market is smaller in 1966 compared with the pattern in 1959, and a new regional market has emerged.

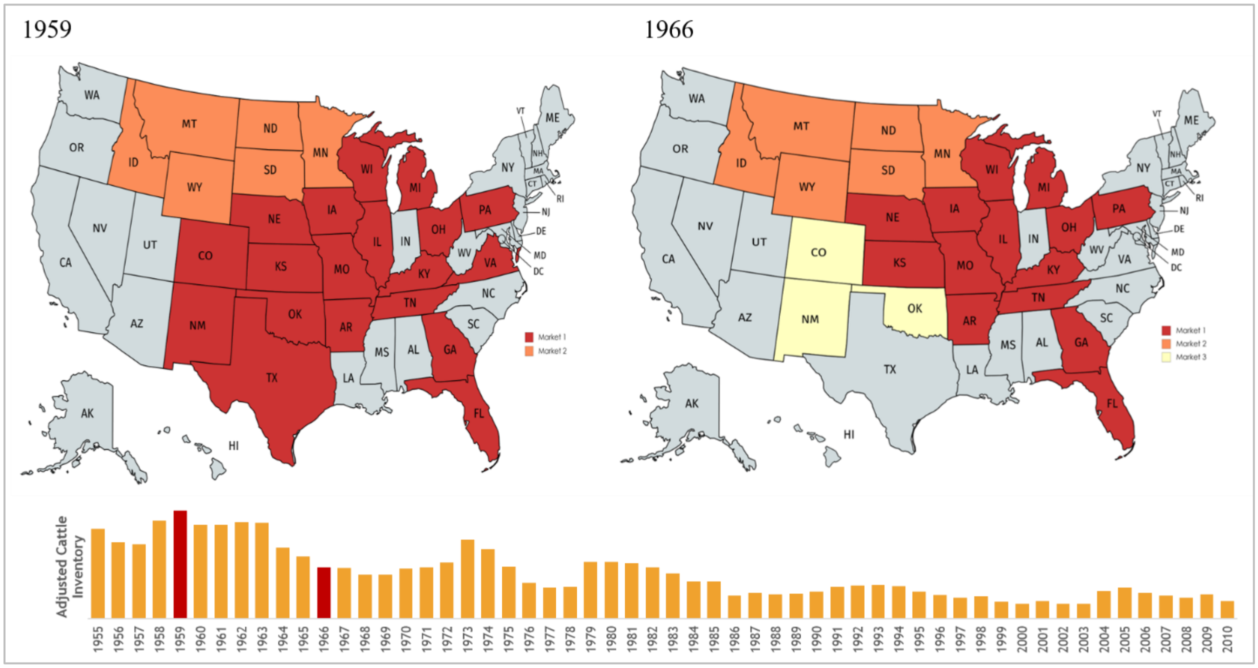

Figure 7 Regional Linkage in 1959 and 1966

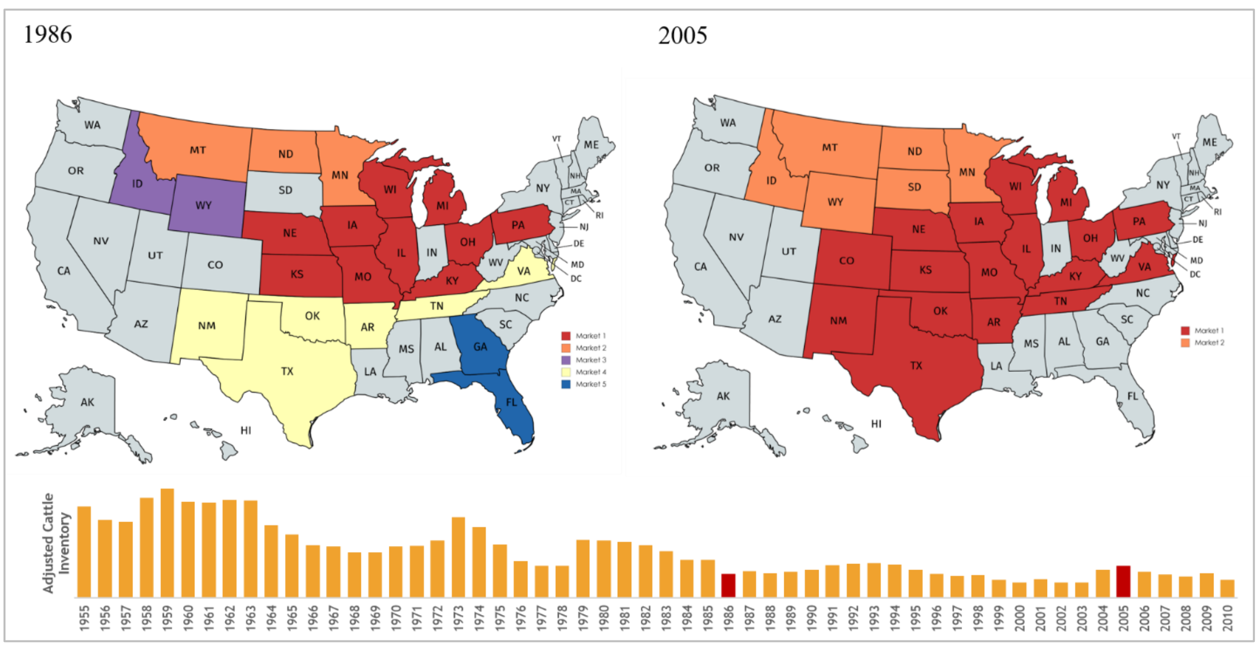

Figure 8 Regional Linkage in 1986 and 2005

As the adjusted level of inventory dropped significantly in the 1980s, the cattle market became even more geographically-segmented. In 1986, there are five distinct regional markets: 1) MT, ND and MN; 2) NE, KS, TX, IA, MO, WI, IL, MI, OH, KY, and PA; 3) ID and WY; 4) NM, OK, TX, AR, TN and VA; and 5) GA and FL. Compared with the linkage pattern of 1959, Colorado and South Dakota have become isolated markets unlinked with any state. Moreover, Arkansas and Tennessee have separated from their previous market and formed a new distinct market with Virginia, New Mexico, Oklahoma, and Texas, while Georgia and Florida unlinked from other markets and formed a small regional market by themselves. For the entire time highlighted, 1986 marks the period of maximum market fragmentation.

More recently, in 2005 when the adjusted level of inventory reached its peak for the decade of the 2000s, there were two distinct regional markets: 1) MT, ID, WY, ND, SD and MN; and 2) CO, NM, NE, KS, OK, TX, IA, MO, AR, WI, IL, MI, OH, KY, TN, PA and VA. That is, the more northern and southern Midwestern previously separate markets linked into one superregional market together with Colorado while the north western regional markets reunited as one regional market. However, Georgia and Florida were no longer linked with any state. Over the whole sample period, we notice CA, AZ, or OR was never linked to any regional market.

Figure 9 presents a visualized table for the value of transition variables. This table is composed of three parts from left to right: a bar chart of adjusted national cattle inventory, the number of linkages in each year, and values of the transition function for selected price pairs. Given the difficulty to read small-sized values in cells, we use scaled color for the numbers of market linkages and for the values of the transition function. The larger the value, the darker the colour is. We find that lower values of the transition function G, which means markets are not linked, always coincide with a low level of cattle inventory. The highlighted areas are the most obvious to observe this correlation.

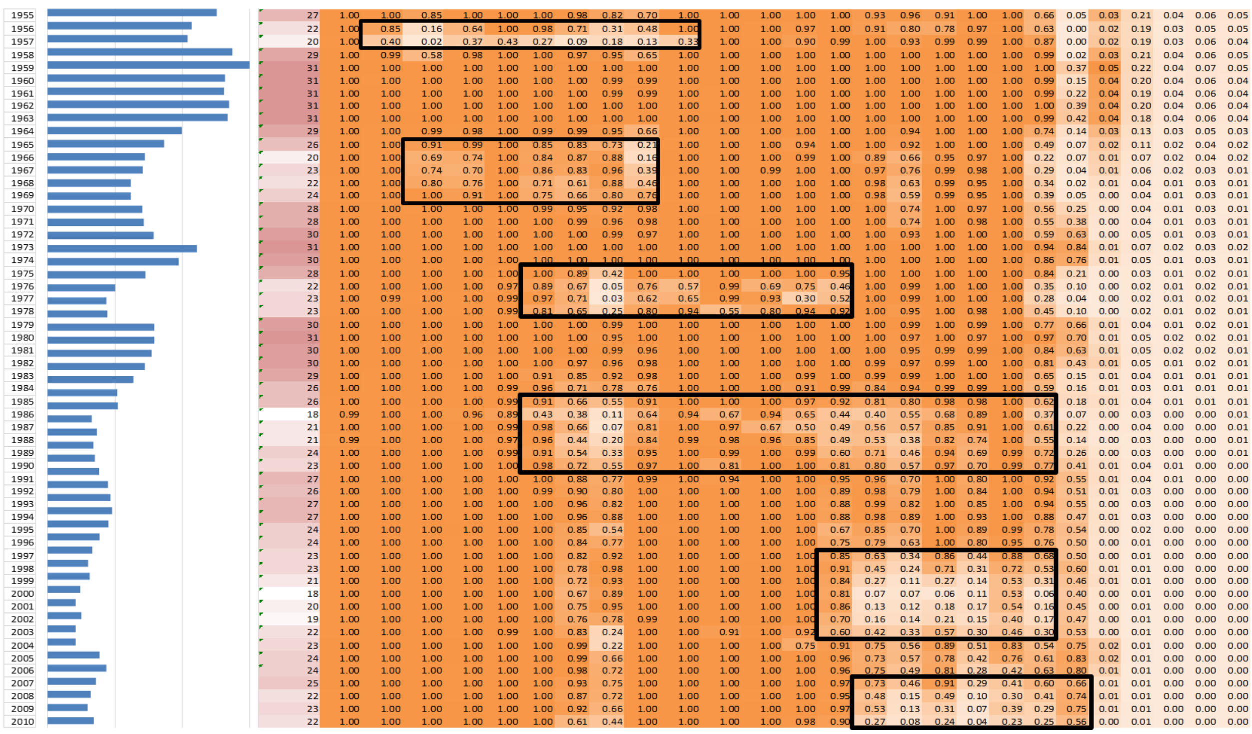

Figure 9 Color-Scaled Values of The Transition Function

c) *Transition Function Results*

For the speed-of-adjustment parameter γ, which ranges from 0.05 to 300, the lower the value of γ, the more slowly the transition function adjusts between linked and unlinked. Transition function values are bounded between 0 (unlinked) and 1 (linked). Figure 10 shows selected results for $\mathrm{G}(s_{it}, s_{jt}, \gamma, \mu)$. For $\gamma < 5$, the transition function adjusts slowly and generally leads to G staying below 0.9, which indicates the state markets are unlinked. For $5 \leq \gamma < 20$, the transition function adjusts at a moderate rate between zero and one, with the integration pattern between two states swinging between linked and unlinked. For $\gamma \geq 20$, the transition function adjusts more quickly, and there are extended periods of time in which the two markets are completely linked. The distribution of these estimated parameters is heavily weighted at the two tails, the integration between states tend to transition either slowly or fast, but moderate speed adjustments are only infrequently observed (Figure 11).

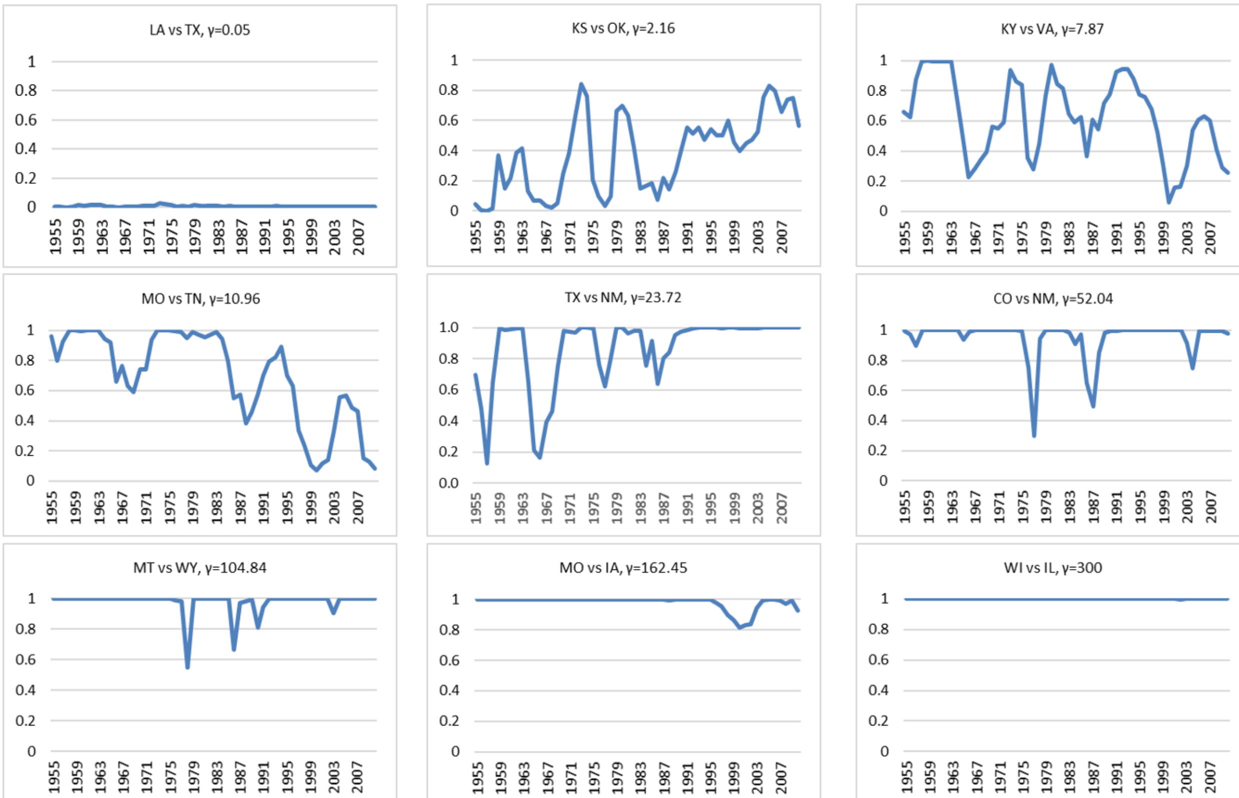

Figure 10 G Function Graphs of Select Price Pairs

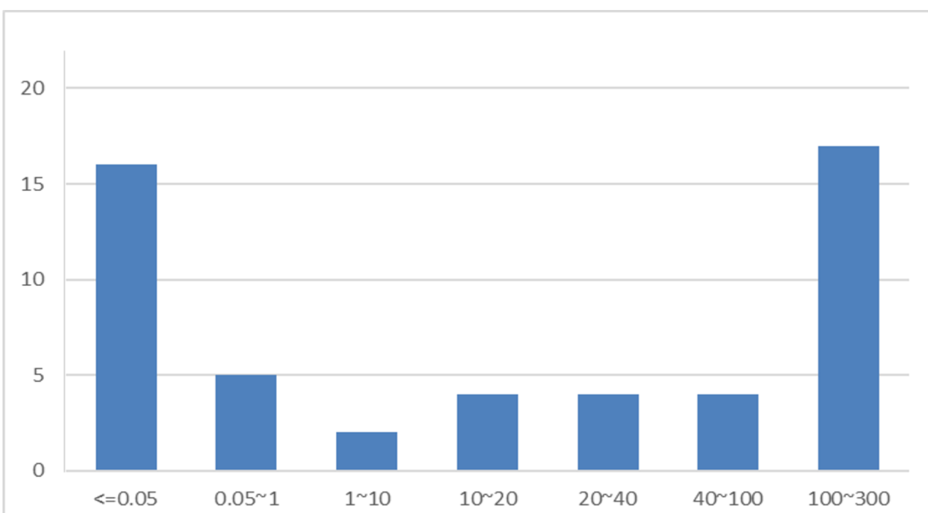

Figure 11 Histogram of γ Values for All Price Pairs

5. Conclusions

This research employed a more flexible transition function that uses a supply-side measure of market activity to help us better understand linkages between regional cattle markets in the U.S. By using cattle inventories divided by annual disappearance as the variable that controls the transitions from integrated to separated markets, we show that excess supply can cause numerous regions and states to link together and function as a single, unified market. Plausibly, when supplies are more available, agents in the market are more motivated to seek profits which then leads to increased trade amongst multiple markets. We find that in the 1950s—the peak of cattle inventory relative to disappearance in U.S. history—apart from two small regional markets, the entire southwestern, midwestern and southern markets are linked into a single geographically enormous market. In contrast, in the mid-1980s, with inventories at their lowest levels, the cattle market became quite segmented, leaving most states as members of one of five regional cattle markets while some of the states exhibited no integrating relationships. After 2003, relative cattle supply rebounded a little, which led numerous states to link together and function as one unified market again. The empirical results show how important sufficient supply and profit-seeking behavior are to ensure spatially separated markets are linked.

Apart from the low level of inventory, an alternative reason for recently segmented cattle market is the increased heterogeneity of beef quality. Empirical results (Lusk and Norwood, 2005) indicate that supply and demand shifts have the potential to alter the average quality of beef on the market. When the assumption of homogeneous products is violated, we should see more segmented markets. For this reason, when two states are not linked, it does not imply no trade of cattle is taking place between these two states. The markets may be unlinked because the states are producing and trading quality-differentiated cattle so that markets are not integrated because there are two (or more) different products in the marketplace, rather than a single, homogenous one.

This paper makes a key contribution to understanding of the degree of spatial market integration in U.S. cattle markets by introducing a supply-side indicator into a time-varying model of regional market integration and by mapping when different regional markets have been linked economically. Moreover, the article contributes to the theoretical literature by modifying an ECON-STAR model so the transition functions better deal with economic indicators at or near their minimum values. Further, our research demonstrated that the ECON-STAR model can be successfully extended to transitions controlled by supply-side variables, which makes the model applicable to many more commodity markets.

CHAPTER 3

ASSESSING THE ROLE OF ORDERING IN SEQUENTIAL ENGLISH AUCTIONS – EVIDENCE FROM THE WESTERN VIDEO MARKET AUCTION

1. Introduction

Cattle prices in the U.S. are established through various market channels, such as direct sales and auction markets. As one of the major price discovery mechanisms, the livestock auction often takes the form of a sequential and multi-object English auction, which is known to be an efficient mechanism in terms of consumer surplus and seller revenue under various assumptions. One often observed phenomenon is that in sequential auctions, the wining prices of homogenous goods tend to decline as the sale proceeds. This has been referred as the 'Declining Price Anomaly', which has been of research interest for decades.

Empirical findings of declining prices in sequential auctions have been reported in multiple studies. In sequential livestock auctions, Buccola (1982) found evidence that the quality-corrected prices of individual cattle lots trend downwards as the sale proceeds. Pitchik and Schotter (1988) experimentally show that prices typically decline due to budget constraints in the course of sequential auctions, given independent private values. Ashenfelter (1989) also found that price declined slightly in sequential auctions of identical units of wine. Empirical studies by McAfee and Vincent (1993) show that the price of the second unit of wine is 1.4 percent lower than that of the first unit on average. Ashenfelter and Genesove (1992) and Beggs and Graddy (1997) took the heterogeneity of objects into account and price decline is still detected. Van Den Berg, et al. (2001) also found the declining price trend in sequential auctions with multi-unit demand in a sequential Dutch auction of roses. The declining price anomaly in sequential auctions was also noted for other objects, for example, Picasso prints (Pesando and Shum, 1982), commercial real estate (Lusht, 1994), satellite transponder leases (Milgrom and Weber, 2000), antiques (Ginsburgh and van Ours, 2007), fish (Gallegati et al., 2011), and lobsters (Salladarre et al., 2017), etc.

A number of theoretical studies explain this declining price anomaly from various perspectives. From the perspective of bidder preferences, McAfee and Vincent (1993) attribute the declining price trend to the non-decreasing absolute risk aversion of bidders. From the perspective of auction structures, Milgrom and Weber (2000) suggest that the use of agents in auctions may explain the declining prices; Black and De Meza (1993) explain this price trend with a buyer's option, which is that the winner of the first auction has the opportunity to buy the remaining objects at the winning price; Von der Fehr (1994) and Menezes and Monteiro (1997) relate the declining price trend to auction participation costs. Engelbrecht-Wiggans (1994), Bernhardt and Scoones (1994), and Gale and Hausch (1994) explain the declining prices from the nature of heterogeneity of the objects in auction. Gale and Stegeman (2001) have theoretically shown that in sequential auctions with two completely informed bidders, prices weakly decline as the auctions progress.

However, opposite empirical results have also been observed. In the analysis of Donald et al. (1997), auction price increases in timber auctions where bidders are interested in more than one object. Jones, et al, (2004) also find prices increase through some sales and decrease through others. Because of the mixed findings from previous auction literature about 'Declining Price Anomaly' phenomenon and limited literature on sequential cattle auctions, in this article, we examine the price trend in the live cattle sequential auction, held by the Western Video Market, Inc. (WVM), based on sales dated from August 2017 to May 2019.

The sequential, asymmetric bidding model of Brendstrup and Paarsch (2006) provides a theoretical platform for both the choice of estimator and the validation of the declining price anomaly in this study. Their model applies to multi-unit, sequential English auctions under the assumption that bidders may value characteristics differently, i. e., the presence of asymmetries. They recognize that the winning bidder will have the highest valuation of that lot and that this valuation can be represented by an order statistic. They specify the distribution of a bidder's highest remaining valuation of a subsequent lot given the number of lots in the auction and the number of lots the bidder has already won. Thus bidders' valuations are asymmetric depending on the number of lots each has won. In our study, we followed their work to show a bidder's expected maximum valuations decreases with the number of the objects he has won. Our empirical model differs from theirs in one important aspect, however. They assume that each potential bidder demands each of the lots in the auction. Clearly this is an unrealistic assumption for the auctions we study—yet with some mild assumptions it can be finessed.

The contribution of this study to existing empirical literature on the declining price anomaly is three-fold: 1) To the best of our knowledge, this is the first research to apply Generalized Extreme Value (GEV) theory to examine English auction data; 2) Instead of evaluating the nominal order number of a lot, we propose a more reasonable representation of relative lot position by using the standardized lot order, which also makes it comparable across sales of various scales; 3) Under the GEV framework, we provide credible empirical findings using the theoretical model of Brendstrup and Paarsch (2006) for the declining price anomaly. This result has important implications for all participants' decisions in a sequential auction including the seller, buyer, and auction organizer, and possibly, for the design of optimal sequential auctions.

This article is outlined as follows: In Section 2, we describe the auction data applied in this study and the characteristics of the video auction. In Section 3, we introduce the Extremal Types Theorem and set up the empirical model. Estimation results are reported and discussed in Section 4. We draw conclusions and provide further discussion in Section 5.

2. Video Auctions and Data Description

Increasingly, large numbers of cattle are being priced through online video auctions. As a major satellite auction operator, Western Video Market (WVM) hosts a live cattle sale in the form of a sequential English (ascending price) auction about every month. In 2016, WVM marketed more than 290,000 head of cattle for more than 850 consignors. As the sale is also broadcast nationwide via satellite and internet, buyers can either attend the sale in person and bid on site or place bids on the telephone or internet. In this way, time and travel costs have been largely reduced and it likely generates a large pool of potential buyers. Previous research has found that satellite video auctions have increased the efficiency of cattle markets, especially in pricing mechanisms. Bailey and Peterson (1991) find that video auction prices were equal to or greater than regional market prices.

Most animals sold on WVM are cattle, including calves, stocker cattle, and bred cows, etc. In very rare cases, lambs are sold as well. A few days earlier than a sale, for each lot detailed information in the form of a sale catalog is available on the WVM website, and it is also distributed electronically and mailed to buyers throughout the country so potential buyers will have the opportunity to study the lots, as well as be informed of the scale of the sale up front. For each lot in a sale, such information includes: the lot number (which determines the position of the lot to be sold during a sale), the lot size (measured in head), average animal weight (measured in cwt/head), sex (steer/heifer/mixed), name of consignor, breed, state of origin, delivery dates, etc. Animals are sold in the unit of a tractor-trailer sized lot and have roughly homogenous characteristics within each lot. Lots are numbered consecutively and the sale proceeds in the order of lot number. In a typical sale, one to two hundred cattle lots are available for sale, with the lot size ranging from 50 head to as many as 1000 head. Some of the lots to be sold are ready for delivery in the next day while some need windows as long as 6 months before they can be shipped.

We collected and pooled the data of historical sales dated from August 2017 to May 2019, during which over 3,000 cattle lots were sold. Sales normally last one day, while big sales may last for two or three days when supplies are abundant. In our analysis, we treated sales that lasted more than one day as several independent sales. For example, the Aug 2017 sale was split into two sales that were held on 7th and 8th. Sales on November 29th, 2017 and March 2nd, 2018 are omitted due to the low trading volumes on these two sales, resulting in 22 sales in the dataset. Given the heterogeneity across cattle lots, we only focus on stocker cattle (500-800lbs) sales, which is a majority type of cattle listed. Moreover, we dropped lots with delivery windows exceeding four months (120 days) from the day of sale, as longer delivery windows are more likely to introduce significant uncertainty. Variables in the dataset include wining prices (in USD/cwt), average weights (in cwt/head), head counts (in hundreds), order of the lot, gender (steer/heifer), state of origin, delivery window (in days). Note that in our analysis, the lot order variable is re-defined as the lot position offered within the subsample of the sale (500-800lbs calves), not within the entire day's sale.

Table 8 summarizes the mean of each variable (except the state of origin) in the sampled data by sale. The overall means of each variable across all sales are reported in the last row. Of all the 1,827 lots sold in the 22 sales, 83 stocker cattle lots were sold per sale on average, with an average price of $157.05 per hundredweight. The mean size of sampled lots ranges from 32 to 158 head with an overall average of 113 head per lot. 61% of the total animals sold are steers. The mean delivery window is 42 days, which is nearly one and a half month. 33 percent of the lots were contract for delivery in over two months (60 days). We also listed the price of the first lot sold in each sale and find that in 19 out of 22 sales, the lots sold in the first place are above the average selling price in that sale. Compared with the overall mean price of $157.05/cwt, the mean price of first lot sold is $174.32/cwt, which is 11% higher. Although not reported, most of the cattle lots offered are from western states – California, Oregon, and Nevada are the top three states that offered 34%, 21%, and 12%, respectively, of the sampled 1,827 lots.

Table 8 Summary Statistics

Date of Sale (22 in total)	Number of Lots (1827 in total)	Mean Price ($/cwt)	1st Lot Price	Mean Weight (cwt/head)	Proportion of Steer	Mean Head	Window (days)	Proportion of Window > 60
8/7/2017	92	147.44	175.50	6.63	70%	98	62	58%
8/8/2017	158	161.12	175.00	5.71	73%	119	73	89%
9/11/2017	111	162.42	150.00	6.38	66%	120	37	15%
10/26/2017	56	159.88	176.25	6.42	53%	116	8	0%
1/4/2018	47	154.59	181.00	6.47	55%	75	7	0%
1/25/2018	46	151.95	170.00	6.53	35%	93	6	0%
4/11/2018	59	154.52	184.00	6.42	57%	113	16	0%
5/3/2018	73	147.96	184.50	7.17	54%	171	16	0%
6/7/2018	41	148.64	172.00	7.00	68%	101	9	0%
7/9/2018	59	154.62	155.00	7.54	66%	128	32	12%
7/10/2018	165	160.56	178.00	6.46	64%	104	79	76%

7/11/2018	83	173.27	167.00	5.58	62%	138	110	99%
8/6/2018	91	153.92	177.50	7.06	62%	106	55	46%
8/7/2018	136	170.67	202.50	5.71	65%	122	77	91%
9/10/2018	133	167.15	160.50	6.39	68%	119	37	14%
10/25/2018	74	154.41	161.50	6.33	55%	93	13	0%
11/28/2018	154	153.05	180.50	6.35	59%	98	14	0%
1/3/2019	64	149.16	186.75	6.22	56%	86	6	0%
1/24/2019	45	147.92	170.50	6.29	51%	104	8	0%
4/10/2019	57	153.88	186.00	6.70	64%	116	27	4%
5/2/2019	51	144.35	165.00	7.23	61%	133	18	0%
5/30/2019	32	133.02	176.00	7.24	66%	116	9	0%
Mean	83	157.05	174.32	6.42	61%	113	42	33%

Based on the characteristics of the video auction held by WVM, we define it is a sequential multi-object English (ascending) first-price auction, where the auctioneer announces the current highest bids to all participants until no higher bid is placed and the winner pays the last price he offered. Since buyers can buy more than one cattle lot, they are defined as multiunit-demand buyers instead of the often-assumed unit-demand buyers. We also assume the buyers' valuations of an object are independent and identically distributed, as the various forms (in-person, online, and on-phone) of participation create an obstacle to forming affiliation among buyers.

Another key element in auction analysis is the number of bidders, which determines the level of competition among the bidders thus playing an important role in buyer's bidding strategy (*i.e.* how high to bid) as well as the selling price, thus the seller's revenue. In the most naïve auction model setting, each bidder is assumed to know the number of bidders, and to know everyone else knows that he knows this. When analyzing video auction, however, it is not appropriate to assume the number of bidders is constant and known to all, especially when the auction is broadcast via internet and satellite so the bidder can enter or exit at any time point of the auction. In our study, this would be less of an issue because the winning price tends to be the highest possible valuation among buyers as the numbers of bidders approaches infinity, regardless of the form of auction (Holt, 1980). Moreover, if information is sufficiently dispersed among the bidders, then the selling price converges to the item's true value as the number of bidders becomes arbitrarily large (Milgrom 1979; Wilson 1977). That is, with perfect competition, the winning price is equal to the true value even though the number of bidders is unknown to all and no individual in the economy knows the true value. In our study, given the scale of the sale and since the sale is broadcast nationwide via internet and satellite, we assume that the number of bidders is sufficiently large although unknown, and as such there is perfect competition among bidders. We also assume each bidder is aware of the large number of bidders and the existence perfect competition.

3. The Extremal Types Theorem and Model Setting

Analogous to the Central Limit Theorem that indicates the mean of a random sample drawn from an arbitrary distribution is asymptotically normally distributed, the Extremal Types Theorem focuses on the asymptotic distribution of the largest/smallest order statistic, or the sample extremes (minima/maxima). Suppose that $X_1, X_2, \dots, X_n$ is a sequence of independent and identically distributed (i.i.d) random variables with a common arbitrary distribution, one way of characterizing extremes is by considering the distribution of the maximum order statistic

$$X^{(N)} = \max\{X_1, X_2, \dots, X_N\}$$

Surprisingly, such distribution of $X^{(N)}$ only falls into one of the three types of distributions: Gumbel (Type I), Fréchet (Type II), and Weibull (Type III) distributions, known collectively as the extreme value distributions (EVD). This fundamental result is known as the Extremal Types Theorem, first discovered by Fisher and Tippett (1928) and then proved in general by Gnedenko (1943). These three distributions can be linked to form an expression which is referred to as the Generalized Extreme Value (GEV) distribution (Von Mises, 1954, and Jenkinson, 1955). The Extreme Value Theory has been widely applied in engineering, environment, especially in disaster studies.

The cumulative distribution function (CDF) and the probability density function (PDF) of the GEV distribution are given by

CDF: $F(z;\mu,\sigma,\xi) =$

$$\begin{cases} \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]_+^{-\frac{1}{\xi}}\right\}, \xi \neq 0 \\ \exp\left[-exp\left(\frac{z-\mu}{\sigma}\right)\right], \xi = 0 \end{cases} \tag{1}$$

PDF: $f(z;\mu,\sigma,\xi) =$

$$\begin{cases} \frac{1}{\sigma}\left(1+\xi\left(\frac{z-\mu}{\sigma}\right)\right)^{-\left(\frac{1}{\xi}+1\right)} \exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]_+^{-\frac{1}{\xi}}\right\}, \xi \neq 0 \\ \exp\left(\frac{z-\mu}{\sigma}\right) \exp\left[-exp\left(\frac{z-\mu}{\sigma}\right)\right], \xi = 0 \end{cases} \tag{2}$$

Where $\alpha_+ = \max(0,\alpha)$. The parameters $\mu, \sigma > 0$, and ξ are the location, scale, and shape parameters respectively. The three EVDs differ in the sign of ξ, which controls the behavior in the tails. When $\xi < 0$, it suggests a GEV distributed random variable has an upper bound, which is a finite value that the maximum cannot exceed, and it gives the Weibull distribution. In contrast, the Fréchet distribution is for $\xi > 0$, which indicates the maximum has a lower finite bound. $\xi = 0$ corresponds to the unbounded Gumbel distribution (Type I), which is also referred to as the log-Weibull distribution, double exponential distribution, and sometimes the Laplace distribution.

Given the fact that the winning price for an object in an English (or ascending price) auction is the maximum bid among all bidders, it naturally motivates us to apply the Extremal Types Theorem to the live cattle auction data. In an auction and among all the bids offered (observable or not), the winning bid always attracts extra research attention. "Since the winning bidder's estimate is the maximum among all the estimates, the winning bid conveys a bound on all the loser's estimates. When there are many bidders, the price conveys a bound on many estimates, and so can be very informative." (Milgrom and Weber, 1982). Now we formally define the settings: in a cattle sale, the winning price for a cattle lot, $p^{(N)}$, is the highest among all the prices, $p_i's$, offered by N bidders: $p^{(N)} = \max\{p_1, p_2, \dots, p_N\}$. $p_i's$ are assumed to be independent and identically distributed, which implies independent valuations among buyers. N is unknown but is assumed to be sufficiently large enough to result in perfect competition among bidders as discussed in Section 2. For each cattle lot at each sale, the CDF of the winning price, p_{it} follows the GEV distribution:

$$F(p_{it}; \mu, \sigma, \xi) = \exp\left\{-\left[1 + \xi\left(\frac{p_{it} - \mu}{\sigma}\right)\right]_{+}^{-\frac{1}{\xi}}\right\}, \xi \neq 0 \quad (3)$$

where p_{it} is the winning price (measured in USD dollars per cwt, \$/cwt) for the i^{th} cattle lot of a date-specific sale, denoted by t. All other parameters are defined the same as in Equations (1) and (2). When we estimate the shape parameter ξ, the standard error for ξ accounts for our uncertainty in choosing between the three types of GEV distribution as it is inconvenient to determine the specific type of distribution upfront in practice. Moreover, the GEV model can incorporate covariates. Specifically, the covariate(s) enter the model through the location parameter, μ,

$$\mu = X\beta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p \quad (4)$$

where X is the covariate matrix and β is the vector of coefficients (including a constant) to be estimated. Note that for GEV distribution:

$$\mathrm{E}(Y) = \mu + \frac{\sigma[\Gamma(1-\xi)-1]}{\xi} = \boldsymbol{X}\beta + \frac{\sigma[\Gamma(1-\xi)-1]}{\xi} \quad (5)$$

The model is estimated by the maximum likelihood method.

4. Empirical Model and Estimation Results

To examine how the winning price responds to the attributes of the cattle being sold, we nest the likelihood function with a hedonic regression. The hedonic price analysis has been used in empirical studies with a long history. Since the paper of Waugh (1928), who studied the influence of quality factors on vegetable price, numerous applications of hedonic price models have been carried out considering very different agricultural and food products. Focusing on cattle, Schroeder et al. (1988) and Bailey and Peterson (1991) used hedonic price models to measure the implicit value of the most important cattle attributes. The basic assumption of the model is the consideration that buyer preferences are based on the sum of the values for cattle, lot, and market characteristics of the good rather than on market goods. In our study, cattle buyers are buying a bundle of separate attributes such as: weight, sex, lot size, days to delivery, state of origin, etc., as they define the value of the whole cattle lot. Specifically, we introduce the following set of attributes in the model for a sale held at date t:

$ORDER_i -$ the relative position of the lot in the sale in lot i. Specifically, this variable is obtained in two steps: First, as discussed in Section 2, we applied specific criteria to the full sample and re-arranged the lot order number to reflect the lot position offered within the subsample of the sale, not within the entire day's sale; Second, we standardized the re-arranged order numbers by subtracting the date-specific mean and dividing it by the date-specific standard deviation. Therefore, the $ORDER_i$ variable reflects the relative position of the lot in a sale and is comparable across sales of various scales. After standardization, the order variable for each sale is within $\pm$ 1.72 standard deviations about zero.

WT_i – the average animal weight in cwt in lot i

$HEAD_i$ – the number of head in lot i divided by 100

STR_i – coded one if lot i is composed of steers (otherwise zero)

$WINDOW_i$ – coded one if the cattle lot i will be delivered in over 60 days, otherwise zero

φ_j – state of origin fixed effects

λ_t – auction date-specific fixed effects

Following Equations (3) and (4), we specify the location parameter, μ, as a linear function of the covariates above:

Model I: $\mu = X\beta = \beta_0 + \beta_1 ORDER_{it} + \beta_2 WT_{it} + \beta_3 HEAD_{it} + \beta_4 HEAD_{it}^2 + \beta_5 STR_{it} + \beta_6 WINDOW_{it} + \varphi_j + \lambda_t$ (6)

We include the quadratic form of head, $HEAD_{it}^2$, to account for the possibility of nonlinear effects of lot size. The price effect of a lot's relative position is represented by β_1, which is the parameter of interest. Given the various forms of participation (*i.e.* internet, telephone, or on-site), it is plausible to assume that the number of bidders for a sale is sufficiently large enough, although unknown, to draw reliable inferences.

a) Empirical Results

Estimated coefficients are obtained by maximum likelihood method and are summarized in Table 9 (estimated fixed effects are not reported, but are available from the authors). All the estimates are statistically significant at 1% level except the window effect and some of the estimated date- and state-specific fixed effects.

Table 9 Parameter Estimates

Variable	Model I	Model II
Intercept	185.516*	185.815*
	(2.217)	(2.220)
Order	-1.459*	-4.944*
	(0.208)	(1.597)
Weight	-8.285*	-8.281*
	(0.271)	(0.271)
Weight*Order		0.534*
		(0.243)
Head	5.250*	5.181*
	(0.413)	(0.411)
$Head^2$	-0.579*	-0.572*
	(0.064)	(0.063)
Steer	13.551*	13.580*
	(0.378)	(0.378)
Window	-0.162	-0.298*
	(0.734)	(0.736)
Scale - σ	7.555*	7.569*
	(0.120)	(0.120)
Shape - ξ	-0.235*	-0.239*
	(0.008)	(0.009)
-2*Log-likelihood	12541	12537
AIC	12617	12615
BIC	12826	12829

As discussed in Section 3, we use standardized order number in the regression as we believe the relative position (or percentile) of a lot in a sale matters more to buyers than its nominal order number, thus making it comparable across sales of different scales (in terms of the number of lots to be sold). In this way, for example, the 40th lot in a sale with 80 lots to be sold is in the same position relative to the 80th lot in a larger-scale sale with 160 lots to be sold. Therefore, the order effect, which is of the interest in this study, measures the mean change in unit price ($/cwt) when the position of a lot of stocker cattle is advanced by one standard deviation, with the other factors remaining constant. Our estimates show that the sale order effect is -1.46 and statistically significant at 1% level. After standardization, the order variable for any sale is within $\pm$ 1.72 sale-specific standard deviations about zero, regardless of the scale of a sale. That is, the last lot is about 3.44 sale-specific standard deviations away from the first lot. Therefore, keeping the other factors constant, the winning price of the cattle lot offered in the last place is estimated to be 1.46*3.44 = 5.02 USD/cwt lower than that of the one offered in the first place, with a standard error of $0.72/cwt. As summarized in Table 8, a typical sale may have an average lot size of 113 head of animals with a mean weight of 6.42 cwt (or 642 pounds) and the first lot price is 174 USD/cwt on average. In such a typical sale, a lot offered in the end of the sale is $1.46\ USD/cwt * 3.44 * 6.42\ cwt/head * 113 head \approx \$\ 3644$ (with a standard error of $522) or $\frac{5}{174} * 100\% \approx 2.9\%$, lower than if it is offered in the very first position.

Average animal weight of a lot has a significant and negative effect on prices: the mean value of estimated mean weight effects indicated that mean price drops $8.29/cwt on average when the average weight increases by one hundredweight. Effects of lot size (HEAD) and quadratic term of head (HEAD2) show a negative relationship between price and lot size and that the speed of price decreasing is faster as the size grows. Steers would be sold at a higher price than heifers by $13.55/cwt on average. As far as delivery window, it shows no significant impact on prices although has negative estimates.

Both the scale and shape parameters are statistically significant and the negative value of estimated shape parameter ($\hat{\xi} = -0.235$) suggests the underlying GEV distribution of the winning price is Weibull (Type III) distribution.

b) Association between Lot Order and Animal Weight

As noted by Buccola (1982), a problem with livestock auction data is that, in most cattle sales, the lot's position is, to some degree, purposely determined by animal weight and/or some other attributes. Thus, measures of the latter factors are often found to be highly correlated with lot position. For example, lot position may be offered in order of ascending animal weight, which is often associated with decreasing unit price ($/cwt). In cases when there exists multicollinearity between lot position and other factors, the magnitude of the position effect on price will be biased down or up, depending on the direction of the correlation. Moreover, the precision of the estimated lot position effect will be decreased, compared with results might be obtained with uncorrelated data. In our sample, we also noticed that in 9 out of 22 sales, the lot position has a highly positive correlation (Pearson's correlation coefficient greater than 0.8) with animal weight (*i.e.* heavier animals are offered in latter positions). Although in Model I, the precision of position effect is not severely affected by multicollinearity given the large sample size, the association between the lot position and the average animal weight motivated us to explore the possible varying order effect due to different animal weight. Therefore, we propose another specification below

Model II: $\mu = X\beta = \beta_0 + \beta_1 ORDER_{it} + \beta_2 WT_{it} + \beta_3 ORDER_{it} \times WT_{it} + \beta_4 HEAD_{it} + \beta_5 HEAD_{it}^2 + \beta_6 STR_{it} + \beta_7 WINDOW_{it} + \varphi_j + \lambda_t$ (7)

where we include an interaction term, $ORDER_{it} \times WT_{it}$, which allows the order effect to vary as the animal weight changes. Maximum likelihood estimation results (except sale- and state-specific fixed effects) are reported in the last column of Table 9. The estimated order effect is now a function of weight, $-4.944 + 0.534 * Weight$, suggesting the magnitude of order effect decreases with average animal weight. Since in our dataset, the weight is restricted between 5 and 8 cwt with an average of 6.42 cwt and the last lot is 3.44 standard deviation away from the first on average, thus the maximum price difference due to order effect ranges from $(-4.944 + 0.534 * 5) * 3.44 = -7.82$ to $(-4.944 + 0.534 * 8) * 3.44 = -2.31$, keeping other factors constant. We also plot the estimated maximum price difference against weight along with the

90% confidence interval in Figure 12. It turns out the estimated mean price effect of Model II given an average animal weight is very close to that estimated by Model I: the estimated mean price difference is $-4.944 + 0.534 * \overline{Weight} = -1.52$ with a standard error of 0.21, if the lot order is advanced by one standard deviation. Therefore, at the historical average animal weight of 6.4 cwt, the mean price difference between the first and the last lots sold is $-1.52 * 3.44 = -5.21$, with a standard error of 0.72. Considering the historical average price of first lot sold is \$174.32, the \$5.21 difference indicates a 3.0% drop. Additionally, all other parameter estimates are very close to those in Model I, except that the coefficient on $Window$ turns out to be negative and statistically significant., indicating on average the price of cattle lots to be delivered in over two months is 29.8 cents lower than that of lots delivered earlier. Likelihood ratio test comparing two models showed results in favor of the model with the interaction term (P-value = 0.027).

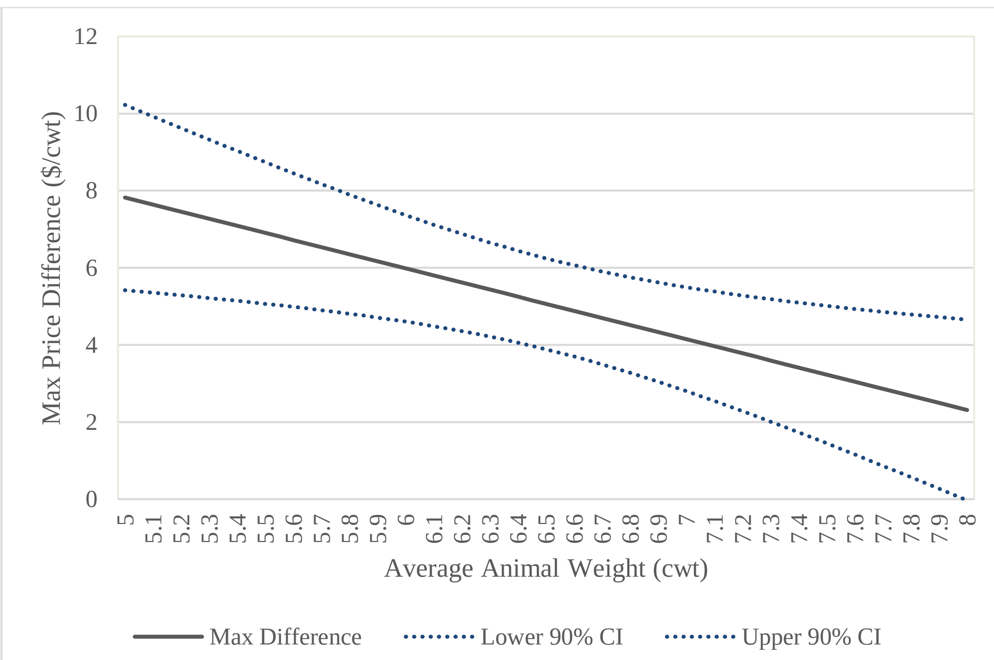

Figure 12 Mean Unit Price Difference (with 90% Confidence Interval) between the First and the Last Lot Sold in a Sale.

c) Declining Price Anomaly Validation

Brendstrup and Paarsch (2006) developed a theoretical platform to investigate how an individual buyer behaves in a multi-unit, sequential English auction. They recognize that the winning bidder will have the highest valuation of that lot and that this valuation can be represented by an order statistic. They specify the distribution of a bidder's highest remaining valuation of a subsequent lot given the number of lots in the auction and the number of lots the bidder has already won. Thus bidders' valuations are asymmetric depending on the number of lots each has won. Our empirical model differs from theirs in one important aspect, however. They assume that each potential bidder demands each of the lots in the auction. Clearly this is an unrealistic assumption for the auctions we study—yet with some mild assumptions it can be finessed.

Following their work, we are able to derive a buyer i's expected maximum valuation toward the subsequent lot, given that there are *m* lots on sale and he already won w_i lots ($m >> w_i$),

$$E(max\ valuation) = \int_0^{Max(Y)} \frac{m!}{(m-w_i-1)!\,w_i!} yF(y)^{m-w_i-1}[1-F(y)]^{w_i} f(y)dy \quad (8)$$

where f(y) is defined from Equation (2), and $F(y) = \exp\left\{-\left[1+\xi\left(\frac{y-\mu}{\sigma}\right)\right]_+^{-\frac{1}{\xi}}\right\}$, is buyer i's cumulative valuation distribution. When $F(y) = 1$, his valuation reaches the highest value, which is

$$Max(Y) = \mu - \frac{\sigma}{\xi}, \qquad \xi \neq 0 \qquad (9)$$

Using Model II, we now have enough information to construct a hypothetical buyer's maximum valuation of a lot. Consider an average expected sale price of $\mathrm{E}(Y) = \$157$. Using the estimated values of $\sigma = 7.569$ and $\xi = -.239$, and following Equation (5), we calculate $\mu =$

$\mathrm{E}(Y) - \frac{\sigma[\Gamma(1-\xi)-1]}{\xi} = 154.11$. And then we plug μ =154 into Equation (9) and can calculate the expected maximum of the distribution is $Max(Y) = 185.78$, which is the upper bound of the integral in Equation (8).

Brendstrup and Paarsch (2006) specify that each bidder is a potential buyer of each of the m lots in the auction. It is likely that buyers have already established their requirements that lots must satisfy due to their production practices and the physical endowments of their operations. In this case we can substitute some assumed value, m^*, for m such that we expect m^* to be considerably less than m. To make this concrete, suppose there are $m = 80$ lots in an auction, and assume that a bidder has a potential interest in 10 lots; hence $m^* = 10$. Given the values expressed above and the GEV distribution assumed, we can evaluate the integral (Equation 8) to observe how a bidder's expected maximum valuations may change in the course of an auction depending on the number of lots won, as shown in the $m^* = 10$ column of Table 10, where we also assessed a buyer's expected maximum valuation given different numbers (m^*) of lots he demanded. The paths of the expected maximum valuation given a buyer's demand are plotted in Figure 13. As a bidder wins more lots, it is clear his expected maximum valuation declines and hence he is less likely to win additional lots. This acts to drive bids down. Our finding that sale prices decline with order is consistent with the empirical findings of Brendstrup and Paarsch who find that the price of the last unit of fish sold declines as the number of units sold increases.

Table 10 A buyer's Expected Maximum Valuation ($/cwt) Given Different Demand (m* lots) and Number of Lots Won (w)

Lots Won (w)	Buyer's Demand (m* lots)								
	10	9	8	7	6	5	4	3	2
0	$ 169.18	$ 168.76	$ 168.27	$ 167.70	$ 167.03	$ 166.19	$ 165.12	$ 163.65	$ 161.39
1	$ 164.95	$ 164.38	$ 163.73	$ 162.95	$ 162.01	$ 160.82	$ 159.23	$ 156.89	$ 152.61

2	$ 162.13	$ 161.44	$ 160.63	$ 159.66	$ 158.45	$ 156.85	$ 154.54	$ 150.47
3	$ 159.84	$ 159.02	$ 158.04	$ 156.83	$ 155.25	$ 153.01	$ 149.11	
4	$ 157.79	$ 156.82	$ 155.62	$ 154.07	$ 151.89	$ 148.13		
5	$ 155.84	$ 154.66	$ 153.14	$ 151.02	$ 147.38			
6	$ 153.87	$ 152.38	$ 150.31	$ 146.77				
7	$ 151.74	$ 149.71	$ 146.27					
8	$ 149.21	$ 145.84						
9	$ 145.46							

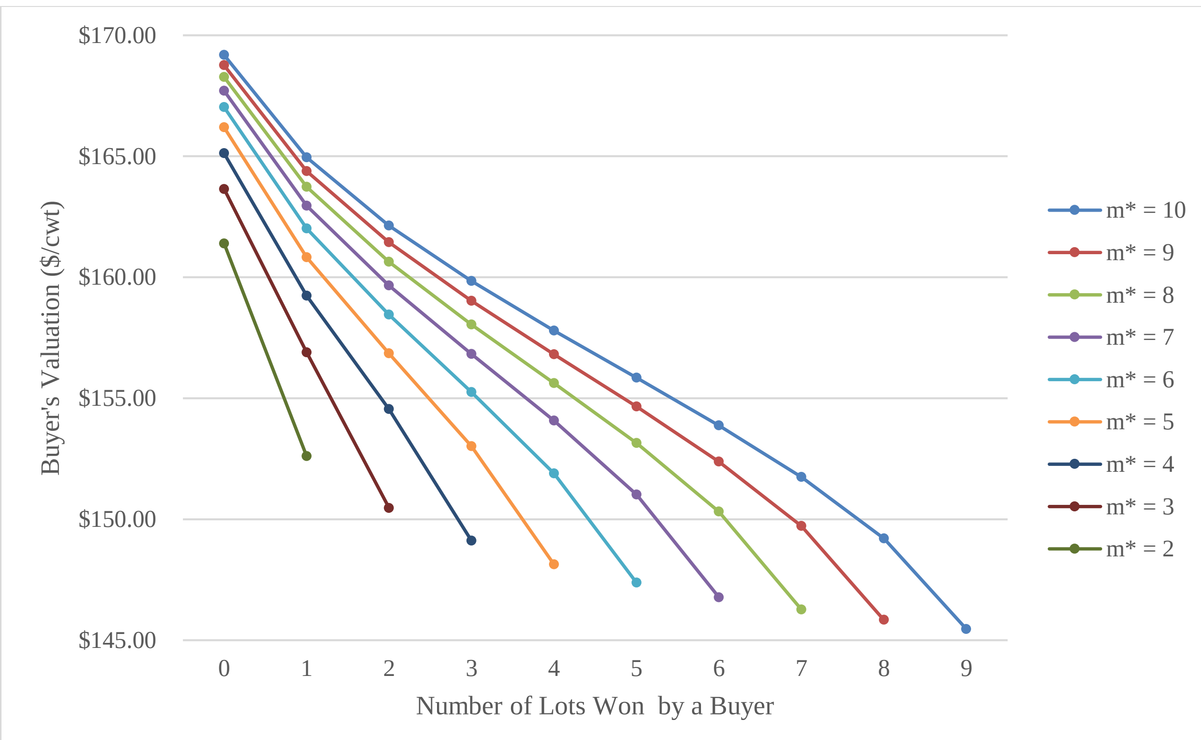

Figure 13 A buyer's Expected Maximum Valuation Given Different Demand (m lots) and Number of Lots Won.

5. Conclusion and Discussion

This article has examined the role of ordering in sequential cattle auctions. It should be expected that at a sequential English auction, the quality-corrected prices of goods tend to decline during the course of the sale. This hypothesis has been tested by examining the winning prices for stocker cattle (500-800lbs) at 22 video cattle auctions dated from August 2017 to May 2019. We proposed two models to fit the auction data based on the Extremal Types Theorem. Both models showed empirical evidence for declining quality-corrected prices at stocker cattle sales. The estimated mean effects of the relative order of a cattle lot in two models are quite close: in the sampled sales, the unit price is estimated to be about $1.5/cwt lower if the relative position of the lot is advanced by one sale-specific standard deviation within that sale. Comparing two identical lots offered in the last and the first position in a sale, it results in about $-5/cwt (or -3%) difference in the total cost, which is a clearly noteworthy drop. The second model with an interaction term between lot order and animal weight is favored because it takes into account the association between these two factors and allows the order effect to vary given changing animal weight.

A mix of factors could result in the price downtrends in a sequential auction. Brendstrup and Paarsch (2006) provided us with a theoretical platform to examine a possible explanation. They developed a framework, which applies to a multi-unit, sequential English auction, to investigate the buyer's expected maximum valuation toward the subsequent object, given the number of objects he demanded and the number of objects he already won. Based on that and assuming a bidder's maximum valuation is from a GEV distribution, we found the bidder's expected maximum valuation actually decreases as the bidder wins more lots, which drives the winning price downward during the course of a sequential auction.

As a consequence, the downward trend in prices indicates that sellers as a group extracted economic rent from buyers, especially during the early phase of a sale. However, the rent is unevenly distributed among sellers: owners of livestock offered early in a sale tend to receive additional gains associated with lot order, while owners whose livestock were offered late in an auction would even suffer losses. In the meanwhile, the sale organizer may take advantage of the downward price trend and could extract the part of gain associated with position from the seller by imposing charges on early positions. In this way, sellers need to pay the organizer higher premium for their items to be sold earlier in a sale. On the buyers' side, the valuation as well as the bidding strategy may be adjusted with the expectation of downward quality-corrected price trend.

Overall, this study made three contributions to the existing empirical literature on sequential auctions: 1) To the best of our knowledge, this is the first research to apply Generalized Extreme Value (GEV) theory to examine the sequential auction data; 2) Instead of evaluating the nominal order number of a lot. We proposed a more reasonable representation of relative lot position by using the standardized lot order, which also made it comparable across sales of various scales; 3) Under GEV framework, we provided justification for one of the possible explanations of declining price anomaly. This result has important implications for all participants' decisions in a sequential auction including the sellers, buyers, and auction organizer, and possibly, for the design of optimal sequential auctions.

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