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The Impact of Extreme Weather on Cattle Feeding Profits

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While large feedlots commonly hedge corn and fed cattle prices, weather remains the largest uncontrollable component of production risk. This research examines the economic losses to cattle feeding associated with extreme weather. Profit losses are assessed using nonlinear regressions that relate weather outcomes, based on the Comprehensive Climate Index (Mader, Johnson, and Gaughan, 2010), and their impact on production variables. Actuarially fair insurance premium rates are derived for an insurance product designed to mitigate the potential cost of extreme weather. Finally, we discuss additional issues associated with using weather-index insurance products and insuring feedlot cattle against adverse weather.

Key words: index insurance, livestock production, weather

Introduction

Cattle feeders in the United States are particularly susceptible to weather events, which can cause sizable losses from animal deaths and adversely impact production efficiency. Despite this susceptibility, no well-developed weather-related risk management products exist for cattle feeders to mitigate this risk. Over 70% of the approximately 25 million head of fed cattle marketed annually in the United States are finished in the Plains region, comprising Texas, Kansas, Nebraska, and Colorado (U.S. Department of Agriculture, National Agricultural Statistics Service, 2013). This region experiences highly variable temperatures with strong winds that result in extremely cold winters and hot summers. While hedging corn and fed cattle prices using forward, futures, and options contracts are common practices for large feedlot operations for mitigating price risk, additional factors—including genetics, breed, animal health programs prior to feeding, management, facilities, and weather—influence profit outcomes. Of these factors, local weather impacts are the most uncertain, can have devastating outcomes, and are not generally insurable.

Extreme weather conditions can cause substantial livestock production losses through increased animal mortality and reduced feeding efficiency and productivity. For example, the severe heat waves of 1995 and 1999 in the Midwestern states caused nearly 5,000 animal deaths in each year (Busby and Loy, 1997; Hahn and Mader, 2002; Hahn et al., 2001). In the Northern Plains states, greater than normal snowfall and wind in the winter of 1996/1997 caused losses of up to 50% of newborn calves and over 100,000 head of cattle (Mader, 2003). In the winter of 2000/2001, feedlot cattle weight gain efficiency and daily weight gain decreased approximately 5% and 10% from previous years as a result of late-autumn and early-winter moisture combined with prolonged cold stress (Hoelscher, 2001). The exceptional drought in the Southern High Plains that began in the fall of 2010 caused

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large economic losses, as calves were forced to be placed earlier than normal in feedlots and breeding animals to be culled at much higher rates than normal or moved to regions where grass and hay were more readily available (Strom, 2013).

While many studies have focused on price hedging in cattle production, only a few studies have analyzed the link between weather-related risks and cattle feeding profits. This may be partly due to the fact that price accounts for more variation than production risk in cattle feeding profits (Belasco, 2008). Additionally, production data are proprietary, and collecting a panel data series with sufficient time and production details to observe a range in weather conditions is especially difficult. Using 15,836 pens of feedlot cattle over a twenty-year span, this research is the first to evaluate the magnitude of weather-related risk in fed cattle production in the United States and provide a framework for computing the maximum amount that a risk-neutral producer would be willing to pay to eliminate this risk.

Motivated by the rise in producer involvement in crop insurance as a means to stabilize incomes for major grain producers, past research has focused on the relationship between weather and crop production risk. Because much of the variability in crop yields emanates from weather-related events, index insurance products have been developed to address this risk (Turvey, Weersink, and Celia Chiang, 2006). Effective index insurance relies on the assumption that weather largely determines crop yield variability with high correlation between adverse weather and low yields. Due to the relatively high correlation, crop losses can be identified using a measure outside of the producer's control, minimizing moral hazard.

In order to characterize a relationship between weather and agricultural production, weather indices are generally based on continuous variables, such as the amount of rainfall, average temperature, or a discrete count of days outside of an optimal threshold (Turvey, 2005). Weather indices are particularly useful for computing a single measure that accounts for the interaction between a set of weather variables and cattle production. The use of weather indices has been applied to livestock in the United States with the development of the Pasture, Rangeland, and Forage (PRF) insurance product for feeder cattle, which is triggered based on one of three indices (rainfall, vegetation, or hay production). One of the complexities of livestock insurance is that there is not a single set of growing days or even a growing season within the year, as is the case with most crops. Because of this, the PRF product is available for different sets of month increments specified by the producer.

Weather-based index insurance products have also been proposed in developing countries. These products would allow participants to collect an indemnity when the index (e.g., rainfall or Normalized Difference Vegetation Index) falls below a specified level. As noted in Chantarat et al. (2013), many index products have been proposed to insure livestock in developing countires due to the mitigation of moral hazard and low cost of implementation and monitoring. Giné, Townsend, and Vickery (2008) notes that many of these products have experienced sluggish adoption. While efforts to develop index-based livestock insurance products in developing countries (e.g., Eithiopia, India, Kenya, Malowi, and Mongolia) have been numerous (see Barnett, Barrett, and Skees, 2008), research efforts to evaluate and develop livestock production insurance products in the United States have been scarce. The lack of livestock production insurance in the United States is especially surprising when one considers the large number of reliable weather stations operating and the well-established insurance networks and heavy reliance on insurance for major grains already in place.

This is the first paper to develop and evaluate the insurability of feedlot cattle in the United States by utilizing the recently developed Comprehensive Climate Index (CCI) (Mader, Johnson, and Gaughan, 2010). The CCI is the first index that accounts for animal stress caused by both hot and cold weather in the feedlot as well as interactions between ambient temperature, humidity, wind speed, and solar radiation. In addition, stress thresholds were developed to accompany the CCI in order to translate index values to weather-related stress in fed cattle. Using this newly developed index, we are able to relate weather-based animal stress to profitability in order to estimate the impact of extreme weather on cattle feeding profits.

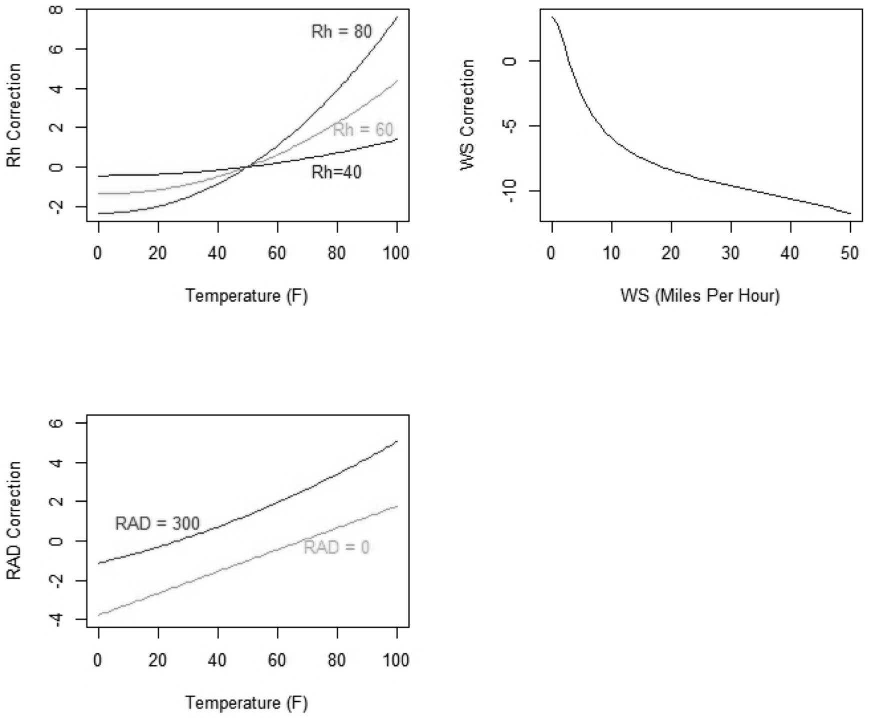

Figure 1. Comprehensive Climate Index (CCI) Correction Factors and Interactions

Measuring Adverse Weather

Past research has noted that there are zones of thermal comfort (ZTC) for farm animals, which vary based on animal-level characteristics such as species or physiological differences, and external factors such as temperature, relative humidity, wind speed, and solar radiation (Ames, 1980; Berman, 2005; National Research Council Committee on Animal Nutrition, 1981; St-Pierre, Cobanov, and Schnitkey, 2003). Positive or negative deviations from the ZTC typically lead to a loss of productivity in livestock and incurring economic losses. Farm animals in the United Statesare often raised in environments where temperature conditions frequently venture outside the ZTC.

Much research in animal science has been devoted to identifying physiological effects of heat stress and the mechanisms by which it reduces animal productivity. During periods of heat stress, cows experience higher mortality rates (Hahn, 1985), a decreased amount of dry matter ingested and digestibility (Lippke, 1975), and a decreased rate of weight gain (Mitlöhner et al., 2001). The extent of production loss is often difficult to estimate because heat stress effects are typically embedded with numerous natural and managerial sources of variation (du Preez, Giesecke, and Hattingh, 1990; Linvill and Pardue, 1992).

Animals exposed to cold weather require more energy to maintain their body reserves and body temperatures (Vining, 1990). In the winter, wind can negatively impact cattle performance, and the effects of wind are magnified when combined with cold temperatures. One way cattle compensate for colder weather is to increase feed intake. However, cattle are physically limited in how much they can consume. Once that physical limit is reached, cattle need higher quality feeds and supplements to compensate for the increased energy requirement.

Prior indices have been applied to account for weather-related animal stress in dairy cows (Deng et al., 2007) and beef cattle (Gaughan et al., 2008; Ames and Insley, 1975). These applications have utilized the temperature-humidity index (THI), which accounts for the replationship between heat and humidity. This index was advanced by Mader, Davis, and Brown-Brandl (2006) by accounting for the impacts of wind speed and solar radiation. Past indices characterizing the impact of cold weather are limited to the windchill index, which was originally developed for humans (Tew, Battel, and Nelson, 2002). This paper utilizes the recently developed Comprehensive Climate Index (CCI) (Mader, Johnson, and Gaughan, 2010), which builds on the previously mentioned efforts. The CCI provides a more flexible index than past efforts because it (1) accounts for both hot and cold weather-related stress, (2) has been calibrated specifically to feedlot cattle stress, and (3) accounts for interactions among ambient temperature (Ta), relative humidity (RH), wind speed (WS), and solar radiation (RAD) through the use of correction factors. Empirical specifications from Mader, Davis, and Brown-Brandl (2006) and Gaughan et al. (2008) were used to establish initial relationships among Ta, RH, WS, and RAD. Using these initial relationships as a starting point, the CCI was developed by collecting a more comprehensive data series, including fifteen years of animal-level stress indicators and environmental data over nine separate summer periods and six different winter periods in which extreme stress events occurred (Mader, Johnson, and Gaughan, 2010). The CCI is computed as

$$(1) \qquad CCI = Ta + Rh^c + WS^c + RAD^c,$$

where RH^c, WS^c, and RAD^c are the correction factors to Rh, WS, and RAD, respectively. The correction factors are

$$(2) \qquad RH^c = e^{0.00182 \times Rh + (1.8 \times 10^{-5})} \times [0.000054 \times Ta^2 + 0.00192 \times Ta - 0.0246] \times [Rh - 30],$$

(3)

$$WS^c = \left[\frac{-6.56}{e^{\left\{ \left[\frac{1}{(2.26 \times WS + 0.23)^{0.45}} \right] \times [2.9 + 1.14 \times 10^{-6} \times WS^{2.5} - \log_{0.3}(2.26 \times WS + 0.33)^2] \right\}}} \right] - 0.00566 \times WS^2 + 3.33,$$

$$(4) \quad RAD^c = 0.0076 \times RAD - 0.00002 \times RAD \times Ta + 0.00005 \times Ta^2 \times \sqrt{RAD} + 0.1 \times Ta - 2,$$

where Ta is measured in celsius, WS is measured in meters/second, and RAD is measured in global horizontal irradiance in watts/meter. The correction factors account for the impact that these weather variables have on animal comfort. For example, high humidity exacerbates high temperatures in animal discomfort, while wind cools animal discomfort under high temperatures but heightens cold stress in times of low temperatures. Additionally, the solar radition correction factor has a nearly linear relationship with temperature. The magnitudes of the correction factors and interactions are illustrated in figure 1 with conversions to standard U.S. units of measurement.

Methods and Procedures

Past studies have noted that pen characteristics such as gender, location, entry weight, and season of placement influence the mean and variance of important animal production performance indicators (Belasco, Ghosh, and Goodwin, 2009; Lawrence, Wang, and Loy, 1999; Schroeder et al., 1993). We add to this literature with the inclusion of publicly observable *ex post* weather variables that can be used to further inform production outcomes.

Observations are split into twelve subgroups to control for the interaction between gender, weight, and time of placement observations and create relatively homogenous groups. Subgroups are split according to two gender groups (steer, heifer), three feedlot placement weight categories (600–700 lb, 700–800 lb, 800–900 lb), and two seasonal placement categories (September–February, March–August). Since feedlots in this region typically vary somewhat in the type of cattle they place at different times of year, we are able to control for breed by creating separate groups for two

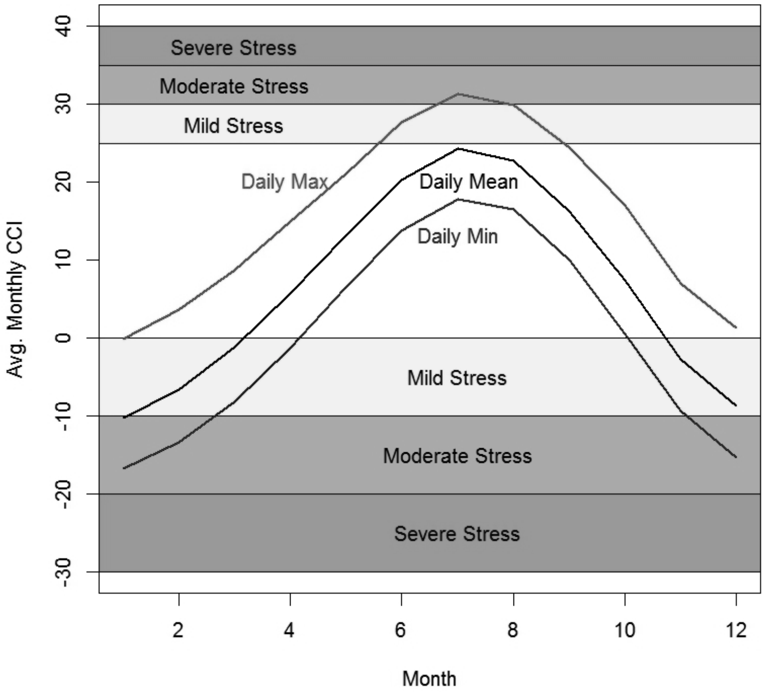

Figure 2. Monthly Average CCI from Nearby Weather Station, 1973–2005

placement periods.[1] Further, an animal's tolerance for exteme weather is influenced by breed and origin.

Once the data are split into relatively homogenous subgroups, regressions are estimated to partially explain production variable outcomes (average daily gain, feed conversion, and mortality rates) with important ex ante variables as well as exogenous weather outcomes. The following model is used to identify the relationship between production variables and weather outcomes:

$$\begin{aligned} Y \quad = \quad & \boldsymbol{\beta_0} + \boldsymbol{\beta_1} HRS + \boldsymbol{\beta_2} HRS^2 + \boldsymbol{\beta_3} HRS^3 + \boldsymbol{\beta_4} HRS^4 + \\ & \boldsymbol{\beta_5} Season + \boldsymbol{\beta_6} lWEIGHT + \boldsymbol{\beta_7} Loc + \boldsymbol{\beta_8} Yr + \varepsilon, \end{aligned} \tag{5}$$

where *HRS* is the number of *Hours* in which a "severe" weather threshold as defined in Mader, Johnson, and Gaughan (2010) was exceeded, based on CCI outcomes, divided by 100; *Season* is a categorical variable that distinguishes between fall, winter, spring, or summer placement season; $lWEIGHT$ is the natural logarithm of entry weight; *Loc* is a binary variable to distinguish between the two feedlots; *Yr* is a linear time trend; $Y = [ADG, FC, MORT]$ and estimates $\boldsymbol{\beta_0}, \ldots, \boldsymbol{\beta_8}$ are each 3×1 vectors. Robust standard errors are also computed in order to account for heteroskedastic errors.

These regressions enable the relationship between weather and production variables to be characterized. We use hours instead of days to characterize weather intensity because this is a more precise measure of weather intensity. The nonlinear model specification is used to provide a flexible model to account for thresholds that occur in production functions while simultaneously nesting more linear models. In order to test the utilized model against alternative specifications, which

[1] For example, placements in late spring tend to originate from southern climates (including Mexico), while fall-winter placements tend to come from northern climates and include breeds—such as Angus, Charolias, Limousin, Hereford, Simmental, and English—that are better suited to handle cold climates. Because breed information is not available, a close approximation is to separate pens by placement timing and entry weight.

included other quantile breaks in *HRS* and polynomial specifications, adjusted R^2 and root mean squared error (in-sample and out-of-sample) were computed.[2]

Mortality rates are modeled in a slightly different manner due to the censored nature of the variable. Since nearly half the mortality rate outcomes result in a zero mortality rate, the Tobit model (Tobin, 1958) is used to consistently estimate the marginal impact of covariates on mortality rates. This methodology follows that of Belasco et al. (2009).[3] Full regression results are reported in Appendices A–C.

Weather Data

In order to evaluate the impact that extreme weather events have on cattle performance, historical weather data from the National Oceanic and Atmospheric Administration (NOAA) and the National Solar Radiation Database (NSRDB)[4] are utilized along with proprietary feedlot cattle production data from two feedlots in Western Kansas.[5] Solar radiation data (RAD) were collected from NSRDB for 1973–2005 and account for global horizontal irradiance (which includes direct and diffuse radition) in watts per meter. Other weather variables—including ambient temperature (Ta), wind speed (WS), and relative humidity (Rh)—were collected from NOAA for 1973–2005. Real-time and hourly historical data are available for all of the weather variables in this index from the High Plains Regional Climate Center and participating state climate offices. Figure 2 shows the average daily maximum, minimum, and mean ambient temperatures by month as well as cattle stress thresholds as defined in Mader, Johnson, and Gaughan (2010). Winter months, especially December, January and February, show a strong propensity for daily mean CCI beyond the mild stress level. Additionally, summer months bring excessively high CCI into mild and moderate stress levels. Both excessively cold and hot conditions are captured in CCI and are used in a similar fashion in our model. However, classifying cattle pens placed by season allows us to distinguish between a pen that is placed in fall versus spring and the different unobservable characteristics that might be implied by these differences (e.g., cattle breed, age, or birth location).

Figure 3 illustrates the median, mean, and ninetieth percentile associated with extreme weather *Hours* for each month. Winter months clearly present more extreme days in sestern Kansas, where the combination of wind and cold temperatures make winter days more uncomfortable. For example, for pens of cattle placed during early January, one can expect 80–100 hours of cumulative severe CCI winter weather stress during January alone. Summer months in this region tend to exhibit high temperatures with reduced stress from low humidity and high wind speed.

After computing the hourly values for all weather variables, weather data are merged into cattle production data to obtain the exact hours each pen was exposed to weather exceeding the "severe" CCI threshold.

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[2] Initially, this study used nonparametric regressions in order to avoid any unnecessary functional form or distiributional assumptions and capture nonlinear relationships and possible thresholds. However, the identification using a nonlinear regression model provided more robust and less overfit results. Nonparametric results were incredibly sensitive to bandwidth specification, which often resulted in overfit models when most bandwidth selection models were used.

[3] While we anticipate that the residuals in each of these equations will be correlated, this is not a concern of this study since the object of interest is the expected profits, which are a function of each of the production outcome variables and will be characterized in a later section.

[4] http://rredc.nrel.gov/solar/old_data/nsrdb/

[5] The production data used in this analysis is augmented with data from a weather station twenty miles from each feedlot. The weather station reports NOAA data that includes hourly ambient temperature, relative humidity, and wind speed. Solar radiation was measured as the total amount of direct and diffuse solar radiation (METSTAT-modeled) received on a horizontal surface during the sixty-minute period ending at the timestamp. More details about METSTAT can be found in Maxwell (1998). Solar radiation data were only available from 1991–2005. Two weather stations with full RAD data series prior to 1991 were used to predict the necessary RAD values. Values were predicted by running a regression from 1991–2005 to relate the station of interest to nearby stations, which were then used to predict missing RAD values plus a standard error correction in order to preserve the given standard error of the series. The adjusted R^2 from the given regression was 0.98.

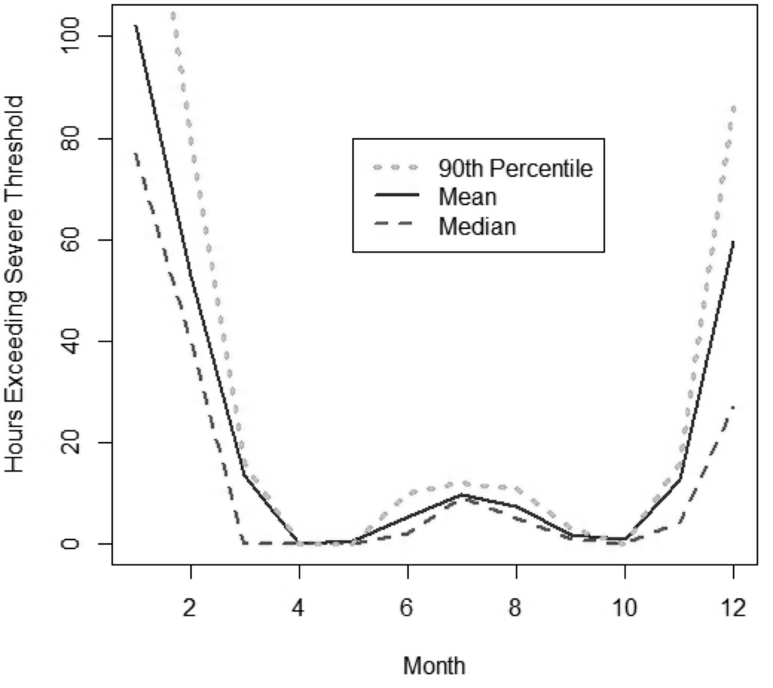

Figure 3. Monthly Boxplot for the Number of Severe Hours According to CCI, by Month, 1973–2005

Feedlot Production Data

Proprietary cattle data were obtained from two large commercial feed yards in western Kansas. The production data include entry and exit information for 15,836 pens of cattle on feed between March 1980 and November 1999. One feed lot contains around 5,000 pens while the other—which is around fifty miles away—represents over 10,000 pens. Table 1 reports summary statistics from the data sample. Animal placement and exit information is collected at the pen-level, allowing for an evaluation into the productivity of each pen with covariate *ex ante* variables of interest such as gender, date of arrival, date of departure, and entry and exit weights. In addition, we collect information on death loss percentage (MORT) and productivity measures of feed conversion (FC) and average daily gain (ADG) for the cattle in each lot.

Mean ADG is 3.14, indicating an average of 3.14 pounds of weight gained per head per day. Average FC of 8.46 indicates that, on average, 8.46 pounds of feed (as fed) is needed to add a single pound of weight gain. MORT indicates the percentage of mortalities in the pen, relative to the number of head entering the feedlot in the pen. Nearly half of mortality values are censored at 0, meaning no death losses. The mean mortality rate for all pens is 0.76% and is 1.53% for pens with non-zero death losses.

Table 2 illustrates the difference in mean statistics by the weather cattle experienced while on feed. Results confirm our hypothesis that animal production performance suffers notably as weather intensity increases: ADG falls while FC and MORT rise. For example, when relative weather intensity moves from ‘Low’ to ‘High’in light weight pens (600–700 pounds), ADG decreases from 3.11 to 2.80 (−10.0%), FC increases from 8.06 to 8.86 (+9.9%), and MORT increases from 0.77% to 1.27% (0.50 percentage points). Each of these weather-related cattle production influences adversely impacts profits, as cattle gain weight at a slower rate (lower ADG), require more feed to gain weight (higher FC), and suffer greater death losses (higher MORT).

Table 1. Summary of Cattle data (n=15,836), 1980–1999

Variable	Description	Mean	Std Dev	Min	Max
ADG	Average daily gain (lbs gain/day)	3.14	0.42	1.39	4.95
FC	Feed conversion (lbs feed/lb gain)	8.46	1.12	5.41	16.71
MORT	Percentage of pen that die, censored observations (n=7,999, 50.51%)	0.76	1.26	0.00	18.75
lWEIGHT	Average weight per head of cattle upon entrance (lbs)	743.59	72.31	600.00	899.85
DOF	Days on feed	129.69	20.21	46.00	240.00
Hours	Number of hours beyond "severe" threshold	93.76	108.10	0.00	514.00
Gender	Percentage of sample	Steer	74.97%	Heifer	25.02%
Season	Percentage of sample	Spring	26.77%	Summer	24.83%
		Fall	27.36%	Winter	21.05%

Table 2. Mean Summary Statistics by Weather Intensity Level

Weather Intensity	n	ADG	FC	MORT	WEIGHT
			600–700 lbs		
Low	1,232	3.11	8.06	0.77	660.94
Mid	1,575	3.03	8.28	0.87	658.22
High	1,963	2.80	8.86	1.27	655.92
			700–800 lbs		
Low	2,383	3.31	8.06	0.55	750.05
Mid	2,487	3.22	8.32	0.60	748.65
High	2,303	2.96	9.01	0.88	747.20
			800–900 lbs		
Low	1,412	3.45	8.26	0.55	840.20
Mid	1,298	3.34	8.60	0.57	838.74
High	1,183	3.08	9.30	0.72	838.33

Notes: Weather intensity levels were determined based on tertiles, where the "Low" intensity includes the lower third of the data where Severe Hours were less than 21, "Mid" includes the middle third which is 21–96 hours, while "High" intensity includes over 96 hours.

Estimation Results and Discussion

Parameters are estimated using least squares estimation with robust standard errors to account for the presence of heteroskedasticity. For brevity, goodness-of-fit statistics are presented in table 3 to provide indicators regarding the ability of included covariates to explain variation in production outcomes. Goodness-of-fit measures include R^2 and Root Mean Squared Error (RMSE) for each of the three animal performance models and ten cattle weight $\times$ gender $\times$ placement season subgroups.[6] Full regression results are available in Appendices A–C.

Results in table 3 are based on randomly selecting two-thirds of the subsample for estimation and using the remaining one-third of the subsample to examine out-of-sample predictive power. This sampling procedure is repeated ten times to provide results robust to outliers. For out-of-sample analysis, the entire one-third is used to compute the "full out-of-sample," while the severest 20% of weather outcomes from the out-of-sample portion is used to evaluate the "tail out-of-sample" portion. Comparisons between these two measures indicate that predicted tail observations, which are often the main emphasis of insurance products, are consistent with the model's ability to predict

[6] Regressions for pens containing heifers with average weights between 800–900 pounds at entry were excluded due to the relatively small number of observations.

Table 3. In-Sample and Out-of-Sample Goodness of Fit Statistics Based on Repeated Random Sampling (m=10), by Subsample

Pen Characteristics				In-Sample Statistics Adjusted R^2			RMSE (in-sample)		
Entry Weight (cwt.)	**Gender**	**Placement Season**	**n**	**ADG**	**FC**	**MORT**	**ADG**	**FC**	**MORT**
6–7	Steer	FW	965	0.290	0.276	0.086	0.320	0.837	1.249
7–8	Steer	FW	1,803	0.200	0.256	0.064	0.326	0.865	1.015
8–9	Steer	FW	1,057	0.144	0.138	0.053	0.365	1.014	0.836
6–7	Steer	SS	680	0.251	0.218	0.057	0.309	0.699	0.918
7–8	Steer	SS	2,007	0.204	0.182	0.029	0.306	0.604	0.776
8–9	Steer	SS	1,280	0.146	0.126	0.045	0.347	0.682	0.751
6–7	Heifer	FW	710	0.193	0.276	0.058	0.299	0.901	1.185
7–8	Heifer	FW	416	0.102	0.133	0.053	0.343	1.022	1.201
6–7	Heifer	SS	825	0.138	0.157	0.050	0.268	0.670	1.023
7–8	Heifer	SS	555	0.103	0.092	0.031	0.297	0.751	0.846

Pen Characteristics				Out-of-Sample Statistics RMSE (Full Out-of-Sample)			RMSE (Tail Out-of-Sample)		
Entry Weight (cwt.)	**Gender**	**Placement Season**	**n**	**ADG**	**FC**	**MORT**	**ADG**	**FC**	**MORT**
6–7	Steer	FW	482	0.326	0.855	1.317	0.353	1.046	1.355
7–8	Steer	FW	902	0.328	0.884	1.066	0.358	1.184	1.142
8–9	Steer	FW	528	0.369	1.027	0.923	0.406	1.247	0.849
6–7	Steer	SS	340	0.364	0.721	1.021	0.478	1.060	1.203
7–8	Steer	SS	1,004	0.309	0.614	0.796	0.291	0.664	0.898
8–9	Steer	SS	640	0.341	0.673	0.767	0.320	0.759	0.726
6–7	Heifer	FW	355	0.299	0.922	1.200	0.344	1.260	1.163
7–8	Heifer	FW	208	0.356	1.048	1.237	0.411	1.356	1.082
6–7	Heifer	SS	413	0.273	0.678	1.087	0.317	0.858	1.266
7–8	Heifer	SS	278	0.300	0.757	0.981	0.306	0.752	1.036

Notes: Based on ten random samples of two-thirds of subsample with remaining one-third used for prediction. Root Mean Squared Error is based on the square root of the summed mean squared difference between actual and predicted values. Figures reported are averaged across ten random samples. Placement Seasons "FW" and "SS" indicate Fall/Winter and Spring/Summer, respectively. For Tobit regressions, the pseudo-R^2 measures based on McKelvey and Zavoina (1975) are used and shown in Veall and Zimmermann (1994) to outperform other pseudo-R^2 measures with censored data. This measure can be written as $R^2_{mz} = \frac{\Sigma(\hat{y}^*_i - \hat{\bar{y}}^*_i)^2}{\Sigma[(\hat{y}^*_i - \hat{\bar{y}}^*_i)^2 + \sigma^2]}$, where $\hat{y}^*_i$ is the predicted latent variable and $\hat{\bar{y}}^*_i$ is the mean of the predicted latent variable. Figures from "tail out-of-sample" are computed from a portion of out-of-sample in top 20% in weather severity.

the the remaining observations. Further, we compare in-sample and out-of-sample RMSE in order to ensure that the model selected is not overfitting the data. Based on these results, overfitting does not appear to be an issue.

For all production outcome (i.e., ADG, FC, and MORT) regressions, lighter weight pens tend to have higher R^2 and lower RMSEs. Conversely, more mature pens are less sensitive to extreme weather conditions, which may result in the models explaining less of the overall variation. Overall, R^2 levels are consistent with results found in livestock insurance applications in developing countries when we consider that in this application, samples are separated and thereby conditioned by placement weight, gender, and placement season prior to running regressions. The reported R^2 measures would obviously be much higher if weight class, gender, and season of placement (i.e., FW, SS) were included as covariates rather than sorting variables. Additionally, as Chantarat et al. (2013) point out, correlations between livestock production indicators and weather are much stronger under adverse weather.[7] The full range of production outcomes is also driven by differences in genetics, animal quality, animal condition when placed on feed, animal health (e.g., respiratory sickness or other diseases), and other environmental factors (e.g., blizzard, hail, variance in weather, etc.). While a select few of these aspects may be accounted for with more detailed data, many of these aspects are unlikely to be revealed or even known by producers who would insure against weather-related production risk for a feedlot. Therefore, it is reasonable to expect a high degree of unexplained variation in these regressions, as would be the case when one compares area versus individual crop insurance plans for major grains. Additionally, typical insurance applications (e.g., health, life, and auto) require a relatively small amount of individual-level information, often amounting to at most 20% explanation of overall variability in outcomes (van Vliet, 1992). Moreover, as we show below, even with a low amount of variation explained or accounted for, the models reveal economically important differences in weather intensity impact across the subgroups, which a properly designed insurance product could affectively address.

The range of R^2 provides insights into how well index-based insurance products would predict livestock losses under adverse weather. Basis risk, which occurs when insurance payments and observed losses do not occur simultaneously, can present a significant obstacle for widespread usage of weather-based insurance products. Thus, a model that relates weather to production outcomes with a relatively low degree of unexplained variation will also decrease basis risk. In this application, pens placed between 600–800 pounds can be more accurately estimated, while heavier placements of 800–900 pounds are more difficult to insure due to the increased basis risk. This result is likely the result of heavier placements being more robust to extreme weather, while lighter placements can be more vulnerable to extreme weather.

Figure 4 shows the fitted values for a fixed amount of *DOF* and variable *Hours*, assuming a steer pen placed in fall with mean statistics from each subgroup. It is apparent that once a threshold of 200 hours of extreme weather is reached, pen-level returns experience adverse impacts from exponentially increasing FC, decreasing ADG, and increasing $MORT$. These three impacts work to magnify the impact on profits. It is also apparent from figure 4 that the functional form assumed allows us to identify these threshold impacts.

Weather Insurance Application

This section uses an example pen and computes the corresponding expected losses related to weather. Expected losses are important in insurance applications as they is equal to the premium rate in an actuarially fair insurance product, which is the maximum amount a risk-neutral producer is willing to pay to eliminate risk. Over the last thirty years, federal crop insurance has become a major tool for insuring individual crop producers against yield and price risk. Area-based crop insurance products, such as Group Risk Plan (GRP) and Group Risk Income Protection (GRIP), have been introduced by the RMA to insure yields and revenue, respectively, based on county-level yield realizations. GRIP is a revenue insurance version of GRP, with guarantees and payments based on the product of county-level yields and futures market prices (Skees, Black, and Barnett, 1997). Recently, the federal government has developed new livestock insurance products such as PRF, which is based on hay production. This is similar to how area crop insurance plans limit moral hazard by tying insurance triggers to a weather index or area-wide measure.

In many crop insurance applications, there may be moral hazard and adverse selection if production is based directly on the production outcomes of the insured. In order to mitigate moral hazard, index insurance is often used, which uses an objective third-party measure as a proxy for individual losses. Most past literature in this area has been focused on developing precipitation or

[7] Chantarat et al. (2013) use a regime-specific linear regression to estimate the relationship between herd mortality rates and a collection of transformed Normalized Difference Vegetation Index (NDVI) variables. The authors also use separate regressions for "good" and "bad" weather regimes and find that adjusted R^2 improves by 50% in "bad" weather regimes relative to "good" weather regimes.

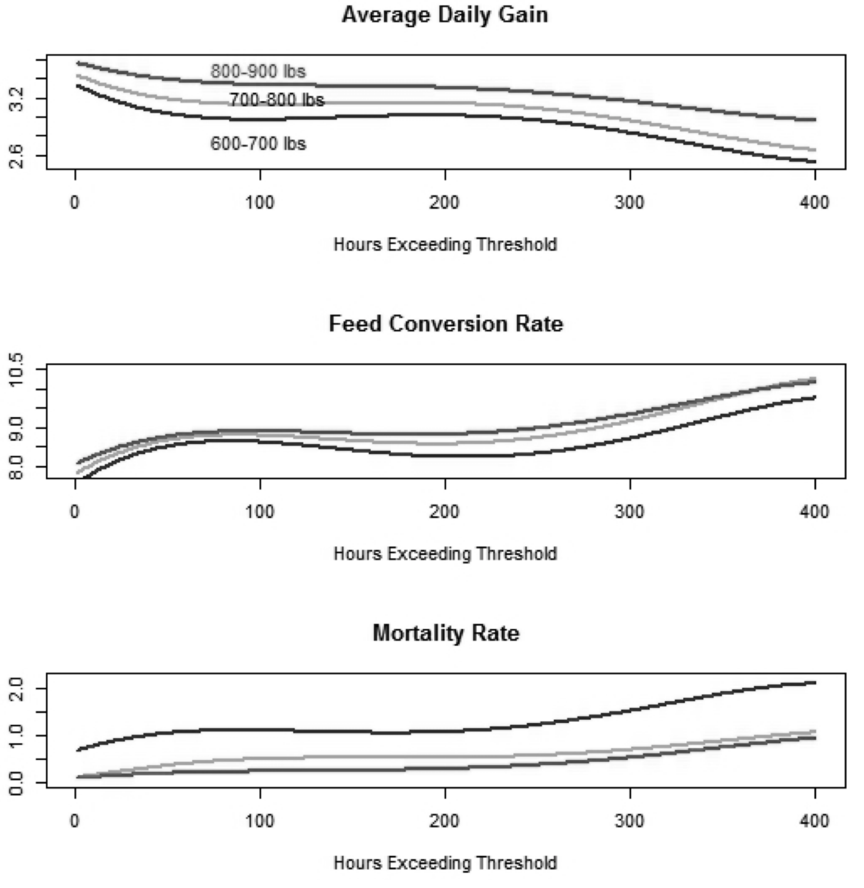

Figure 4. Predicted Values of Dependent Variables from Fall Steer Placements, by Weight Class

heat indexes for crop insurance (Barnett and Mahul, 2007; Deng et al., 2008; Martin, Barnett, and Coble, 2001; Turvey, 2005; Vedenov and Barnett, 2004).

Weather-based insurance products provide an indemnity payment to the insured agent when the observed outcome is above a specified strike. Similarly to crop insurance applications, the strike could be specified by the insured agent and influences both the premium rate and expected indemnity. In our application, the indemnity is based on the number of hours the CCI threshold exceeds the strike. This type of an insurance product would be provided to compensate fed cattle producers in the event of production losses due to extreme heat or cold weather. In order to compute the premium rate associated with such a product, we need to determine the product of the probability of the event occurring and the expected loss given that the event occurs to determine the actuarially fair premium. To compute the expected losses given extreme weather, we use a regression technique similar to that in Vedenov and Barnett (2004), who regress yields on average monthly temperature, monthly precipitation, and the interaction between the two for the months of June, July, and August. In this application, the use of the CCI to determine the existence of extreme heat or cold weather is supported by the research provided by Mader, Johnson, and Gaughan (2010), which was calibrated using times when extreme cold and heat were experienced.

We first compute the expected loss, conditional on the adverse event occuring. This is a bit trickier that it would seem at first glance since there can be an array of hours over the threshold. Since extreme hours are measured discretely, we construct the expected loss function in the following manner:

$$E[loss|hours > D] = \sum_{h=1}^{H} pr[hours = D + h] \times E[loss|hours = D + h], \tag{6}$$

where h is the number of hours over D and H is the maximum hours considered and may be thought of as an upper limit after which additional hours have no marginal influence on production variables or is sufficiently close to a zero probability of occurance. We next focus on estimating expected losses conditional on weather using production data from 1980–1999 and the probability of loss using weather data from 1973–2005.

Expected Losses from Extreme Weather Events

ADG, FC, and $MORT$ are all functionally dependent on HRS. For this reason, the impact of an additional hour of extreme weather on profits has a nonlinear impact that is related to the impact of HRS on ADG, FC, and $MORT$ as well as the profit function. Because of this we can estimate the impacts of a one-unit change in *Hours* on profits by using a baseline scenario and a treatment scenario where we increase *Hours* and hold other placement variables constant. This allows us to identify the lost profit due to extreme weather.[8]

In order to examine the expected loss, we first use a profit function based on Belasco (2008). This profit function can be specified as

$$P = TR - FDRC - YC - FC - IC - VCPH; \tag{7}$$

$$TR = FP \times CSW \times (1 - MORT); \tag{8}$$

$$CSW = (0.96) \times CPW + ADG \times DOF; \tag{9}$$

$$FDRC = FRP \times CPW; \tag{10}$$

$$YC = (0.40) \times DOF; \tag{11}$$

$$FC = CP \times \left\{ \tfrac{DMFC}{0.88} [CWS \times (1 - MORT) - CPW] \right\}; \tag{12}$$

where P are per head profits, TR is the total revenue per head from cattle feeding, $FDRC$ is the per head cost of purchasing feeder cattle, YC is the per head fixed cost (yardage cost) of feeding cattle, FC is the per head feed cost, IC is an interest cost, $VCPH$ are the per head costs associated with veterinary care, FP is the price per hundredweight (\$/cwt) of fed cattle, CSW is the average sell weight of the finished cattle, FRP is the price per hundredweight (\$/cwt) of feeder cattle, CP is corn price, CPW is the average weight of the feeder cattle at placement, and DOF is the number of days the pen of cattle is in the feedlot. This profit function assumes a 4% live-weight shrinkage factor to reflect the expected loss in weight during transportation from feedlot to packing plant, a fee of \$0.40 per head per day for custom feeding (YC), and 12% moisture contained in the corn-based feed ration.[9] Based on this function, we can see that the performance indicators impact cattle sell weight (CSW), total revenue (TR), and feed cost (FC).

We now provide a specific example. We assume a steer pen, placed on feed averaging 750 pounds, on feed for 130 days, and placed in fall. The assumed price of corn is \$4.00/bushel, the fed cattle price is \$140/cwt, and the interest rate is 5.0%. While these variables are all held constant in

[8] There are likely to be additional impacts of weather on quality that we are not able to estimate with the given data. Thus, the presented results may slightly understate total losses due to weather.

[9] The given shrink rate is consistent with ranges presented in related studies (Coffey et al., 2001; Gill, Barnes, and Lalman, 2014). These given shrinkage rates reside on the low end of the observed shrinkage rates due to increases in shrinkage that occur due to distance traveled, diet, and weather, among others (Gonzalez et al., 2012). Yardage fees are estimated to be \$0.40 per head per day, which is also consistent with related studies (Gill, Barnes, and Lalman, 2014; Kumar et al., 2012). The marginal results presented in the present study are robust to substantial changes in yardage cost and shrink rates.

Table 4. Scenario Results from Example Pen to Examine the Impact of *Hours* on Profitability

Metric	Units	Scenario 1 Hours = 200	Scenario 2 Hours = 400	Change
Sell Weight	lbs	1,085.18	1,027.84	−57.33
$E(ADG\|Hours)$	lbs/day	3.06	2.58	−0.48
$E(FC\|Hours)$	lbs feed/lbs gain	8.81	10.37	1.56
$E(MORT\|Hours)$	mortalities/head	0.82%	0.95%	0.12
Revenue	$/head	1,506.75	1,425.37	−81.38
Feed Cost	$/head	114.96	111.25	−3.71
Interest Cost	$/head	1.33	1.30	−0.03
Profit	$/head			−77.64

this analysis, we compare our sample pen when *Hours* = 200 and *Hours* = 400, which approximately corresponds to the empirical median and eighty-eighth quantile for the subsample of interest. We can think of the median *Hours* within this subgroup as the anticipated ex ante returns from a normal weather-related year. The results are shown in table 4. Adverse weather is expected to decrease *ADG* by nearly half a pound (0.48) per day, increase *FC* by 1.56 pounds of feed needed for each pound of weight gain, and a substantial increase in *MORT* by 0.12 percentage points. Each of these performance changes negatively impacts cattle feeding profits. For this particular simulation, the incremental increase of 200 additional *Hours* of extreme weather results in a profit reduction of $77.64/head. Revenue is reduced by $81.38/head from reduced ADG and increased MORT, which is a 5.4% reduction in revenue. Feed costs and interest costs also have slight impacts.

Based on twelve years of historical feedyard net returns (January 2002–April 2014), Tonsor (2014) estimates the average return per head is −$33 for steers and −$21 for heifers. Thus, the loss of $78/head is a relatively large loss for a business based on low margins and high volume. Additionally, the losses from weather are aggregated across the pen, which in this data averages around 135 head. Using the case of a 135-head pen, a per head loss of $78 translates into substantial losses of around $11,646/pen.

To provide more general results, figure 5 shows lost profit if we vary severe weather *Hours* from 200 to 400 over a feeding period. The marginal losses are steep along this range. The next subsection evaluates the likelihood of such an event occurring in order to compute expected losses.

Distribution of Hours above Extreme Weather Events

We next compute the probability of *Hours* exceeding *D* for a certain feeding period. We use an example of a pen with an average placement weight of 750 pounds that is placed on feed for 130 days from November 1 to March 7 (the average number of days on feed for subsets contained within this group). Using weather data from 1973–2005 (thirty-two years), the empirical histogram of *Hours* is computed for the days in our example pen (figure 6). Given the relatively short time series used for this weather, we characterize the empirical distribution using a lognormal distribution with the associated mean and variance from the empirical distribution. Using a lognormal distribution eliminates some of the lumpiness in the distribution that arises from a relatively small sample and simplifies the computation of the integrals. The estimated lognormal distribution is also shown in figure 6. There are more than 200 hours 48.77% of the time, while more than 400 hours occurred 10.98% of the time. Given this information, this type of weather event is relatively unlikely, although very costly in terms of lost profits.

Using equation (6), we combine the historical weather information with the expected lost profits to determine the actuarially fair premium rate or expected losses. Results are shown in table 5 with varying strike levels at 200, 250, 300, and 350 hours, which results in respective premiums of $8.50, $8.04, $6.22, and $3.27 per head. Each strike level corresponds to the given quantile, which provides

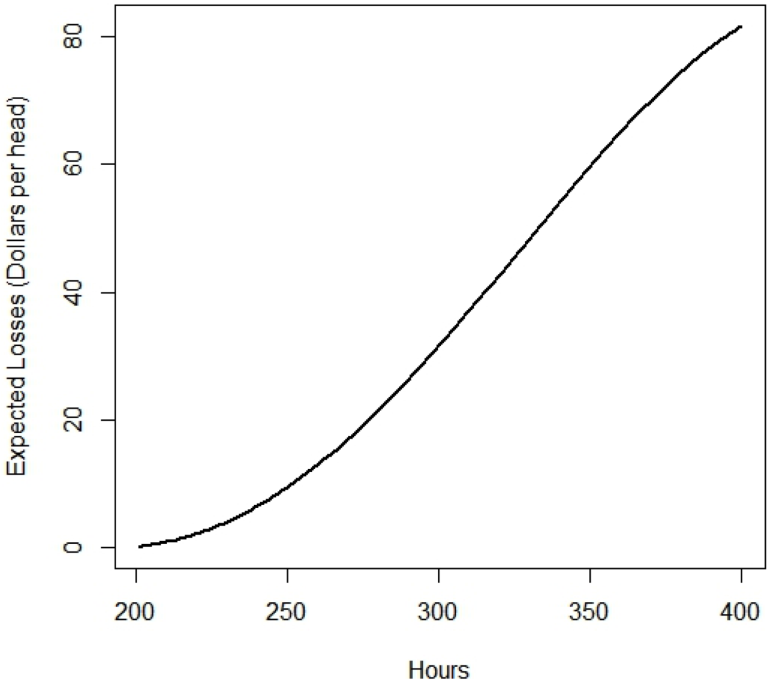

Figure 5. Expected Losses per Head, Relative to 200 Severe Hours

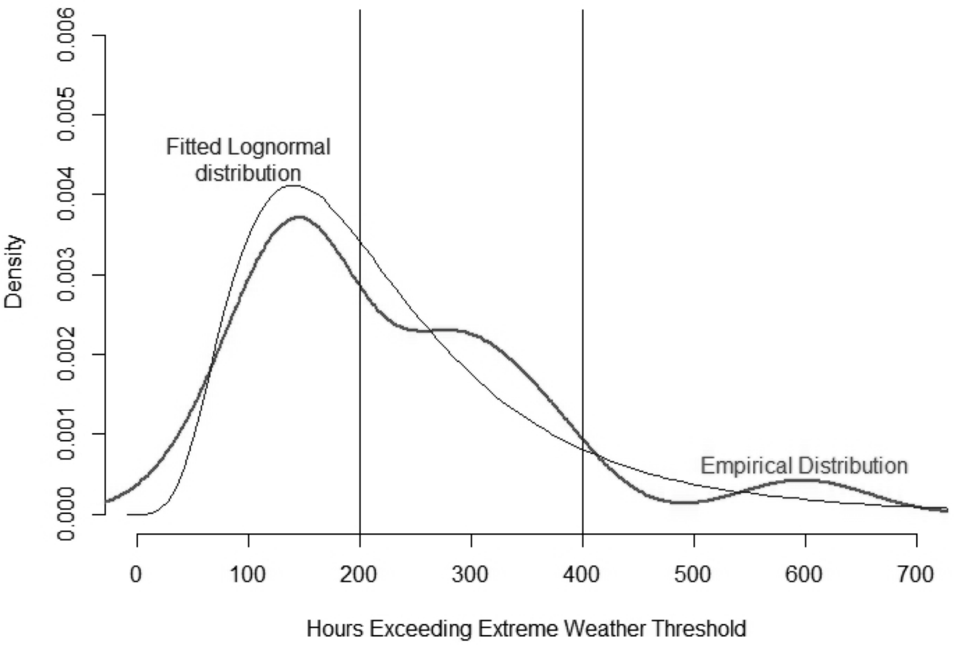

Figure 6. Empirical Distribution of Hours between November 1–March 7 in Western Kansas Location, 1973–2005

Table 5. Premiums Associated with Different Strike Levels from Example Pen

Strike	Strike Quantile	Premium ($/head)
200	51.33	8.50
250	66.15	8.04
300	76.11	6.22
350	83.99	3.27

Notes: Example pen is a fall steer pen placed with an average weight of 750 pounds, on feed for 130 days, corn price of $4.00/bushel, fed cattle price of $140/cwt, and an interest rate of 5%.

the probability of an outcome being less than the strike. As expected, higher strikes give the insured agent a lower chance of an indemnity payment, a lower expected indemnity, and therefore a lower premium.

Conclusions

This study evaluates the economic impact of extreme hot and cold weather conditions on three cattle performance variables–*ADG*, *FC*, and *MORT*—using 15,836 pens of cattle in Western Kansas over twenty years. One difficulty with this research is selecting weather indices to capture extreme hot and cold weather events. Results indicate that weather stress has economically significant impacts on cattle feeding profits, especially during times of severe weather. An example pen is used to illustrate how these results might be used to assess economic losses in feeding cattle associated with extreme weather. This application then leads to the development of a derivative product to insure against weather-related livestock losses. The adoption of this new Comprehensive Climate Index (CCI) provides a promising avenue of further research to develop weather insurance products for feedlot producers.

While this research provides a framework for evaluating a cattle feeding insurance derivative, it is not without need for refinement. First, not all weather components that influence animal production are included in this model. Other variables that may be of interest in a weather index include the impacts of precipitation and mud. The feedlots in our study are located in an area that is relatively arid and has a sandy soil, so the issues of excessive precipitation and mud would likely have more impact in other regions. The question also remains as to how a researcher should incorporate threshold analysis using an index. For example, is it more important to monitor extreme stress or continual slight stress?

Second, basis risk is an area of concern in this particular research and has plagued all area-based insurance products (Smith and Watts, 2009). In order to minimize basis risk, more accurate weather prediction methods would likely improve the prediction of weather at a point. The main problem with weather-index products is that weather stations are not installed at all production areas. So, weather at a point is predicted based on the surrounding weather data, which may not be adequate. In this region, which is especially dense with feedlots, the closest weather station is fifteen miles away from the production areas used. Using additional weather station data and incorporating spatial dynamics may be helpful to minimize basis risk. This issue is more acute in applications within developing countries where weather stations are more sparsely located.

Third, other measures can be taken to reduce weather-related animal performance impacts in areas where weather is expected to place stress on animals with more frequency, such as windbreaks in northern areas and shade in southern areas. While this research provides a framework from which to evaluate the value of these self-insurance methods, they inevitably would change the production responses to weather. Results from this research provide insights into the relative costs and benefits associated with taking such measures to mitigate weather-related effects on production.

Fourth, weather is likely to have a significant impact on quality and yield grade outcomes as well as dressing percentage of harvested animals. Our research evaluates the impact of weather on live weight pricing methods. However, given that many producers utilize grid pricing and dressed weight pricing methods, additional weather-related risk factors may persist and require additional insight.

Fifth, the demand for domestic livestock insurance is an area of research that has received little attention. This is surprising given the extensive literature evaluating the demand for crop insurance in the United States, as well as index-based weather insurance products in developing countries. Many of those applications have focused on surveys of potential users. While this research does not evaluate the demand for livestock insurance products, experimental research could provide context to evaluate potential utilization rates.

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Table A1. Appendix A. Estimation Results: Average Daily Gain (ADG)

	Gender: Steer						Gender: Heifer			
	Placement: Fall/Winter			Placement: Spring/Summer			Placement: Fall/Winter		Placement: Spring/Summer	
Weight Class	600–700	700–800	800–900	600–700	700–800	800–900	600–700	700–800	600–700	700–800
Intercept	−4.429***	1.814	−5.582***	−2.685	−3.166***	1.531	1.282	1.253	3.636***	3.936**
	(1.355)	(1.142)	(1.943)	(1.652)	(1.028)	(1.708)	(1.405)	(2.467)	(1.207)	(1.999)
HRS	−0.975***	−0.822***	−0.544***	−0.659***	−0.409***	0.078	−0.791***	−0.596***	−0.577***	−0.368
	(0.099)	(0.069)	(0.106)	(0.131)	(0.100)	(0.213)	(0.099)	(0.166)	(0.138)	(0.261)
HRS^2	0.870***	0.723***	0.443***	0.444***	0.125	−1.319**	0.722***	0.522***	0.369*	0.267
	(0.092)	(0.067)	(0.101)	(0.151)	(0.172)	(0.545)	(0.095)	(0.16)	(0.214)	(0.710)
HRS^3	−0.294***	−0.246***	−0.151***	−0.148***	−0.001	1.164***	−0.255***	−0.182***	−0.139	−0.143
	(0.031)	(0.023)	(0.035)	(0.057)	(0.095)	(0.439)	(0.033)	(0.056)	(0.102)	(0.611)
HRS^4	0.031***	0.026***	0.016***	0.016***	−0.004	−0.277***	0.028***	0.020***	0.018	0.019
	(0.003)	(0.003)	(0.004)	(0.006)	(0.015)	(0.104)	(0.004)	(0.006)	(0.015)	(0.15)
Winter/Summer	0.191***	0.065***	−0.033	−0.072***	0.037***	0.071***	−0.009	−0.119***	0.094***	0.138***
	(0.019)	(0.014)	(0.021)	(0.022)	(0.012)	(0.016)	(0.021)	(0.032)	(0.016)	(0.021)
lWEIGHT	1.064***	0.162	1.140***	0.881***	0.811***	0.082	0.203	0.211	−0.112	−0.300
	(0.206)	(0.173)	(0.290)	(0.250)	(0.158)	(0.256)	(0.214)	(0.377)	(0.187)	(0.303)
Loc	0.023	−0.050***	−0.004	−0.136***	−0.165***	−0.164***	−0.030	0.136***	−0.086***	−0.045**
	(0.018)	(0.014)	(0.022)	(0.022)	(0.012)	(0.019)	(0.020)	(0.030)	(0.016)	(0.022)
Yr	0.009***	0.006***	0.015***	0.005**	0.015***	0.016***	0.005**	0.004	0.001	0.011***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
R^2	0.288	0.204	0.147	0.255	0.206	0.147	0.207	0.108	0.147	0.100
RMSE	0.322	0.326	0.366	0.308	0.307	0.344	0.298	0.347	0.269	0.297
n	1,447	2,705	1,585	1,020	3,011	1,920	1,065	624	1,238	833

Table A2. Appendix B. Estimation Results: Feed Conversion Rate (FC)

	Gender: Steer						Gender: Heifer			
	Placement: Fall/Winter			Placement: Spring/Summer			Placement: Fall/Winter		Placement: Spring/Summer	
Weight Class	600–700	700–800	800–900	600–700	700–800	800–900	600–700	700–800	600–700	700–800
Intercept	−3.195	−13.088***	−5.482	5.584	−0.930	−11.438***	−16.189***	−21.957***	−6.351**	−23.228***
	(1.355)	(1.142)	(1.943)	(1.652)	(1.028)	(1.708)	(1.405)	(2.467)	(1.207)	(1.999)
HRS	3.223***	2.860***	2.288***	1.353***	0.472**	−1.398***	3.064***	2.400***	0.434	−1.004
	(0.099)	(0.069)	(0.106)	(0.131)	(0.100)	(0.213)	(0.099)	(0.166)	(0.138)	(0.261)
HRS^2	−3.075***	−2.694***	−2.079***	−0.862**	0.359	6.437***	−2.984***	−2.030***	0.504	3.340*
	(0.092)	(0.067)	(0.101)	(0.151)	(0.172)	(0.545)	(0.095)	(0.160)	(0.214)	(0.710)
HRS^3	1.036***	0.925***	0.717***	0.282*	−0.268	−5.418***	1.052***	0.679***	−0.270	−2.221
	(0.031)	(0.023)	(0.035)	(0.057)	(0.095)	(0.439)	(0.033)	(0.056)	(0.102)	(0.611)
HRS^4	−0.108***	−0.098***	−0.077***	−0.031*	0.045	1.276***	−0.113***	−0.071***	0.040	0.461
	(0.003)	(0.003)	(0.004)	(0.006)	(0.015)	(0.104)	(0.004)	(0.006)	(0.015)	(0.150)
Winter/Summer	−0.549***	−0.342***	−0.081	0.151***	0.082***	0.021	−0.164***	0.161	−0.096**	−0.169***
	(0.019)	(0.014)	(0.021)	(0.022)	(0.012)	(0.016)	(0.021)	(0.032)	(0.016)	(0.021)
lWEIGHT	1.958***	3.235***	2.226***	0.171	1.254***	2.720***	3.737***	4.447***	1.836***	4.607***
	(0.206)	(0.173)	(0.290)	(0.250)	(0.158)	(0.256)	(0.214)	(0.377)	(0.187)	(0.303)
Loc	0.092*	0.271***	0.202***	0.362***	0.452***	0.448***	0.118**	−0.283***	0.198***	0.067
	(0.018)	(0.014)	(0.022)	(0.022)	(0.012)	(0.019)	(0.020)	(0.030)	(0.016)	(0.022)
Yr	−0.020***	−0.005	−0.015***	0.009*	0.003	0.014***	0.000	0.011	0.029***	0.017**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
R^2	0.273	0.259	0.140	0.223	0.183	0.130	0.287	0.136	0.162	0.092
RMSE	0.841	0.871	1.017	0.688	0.606	0.678	0.907	1.028	0.671	0.752
n	1,447	2,705	1,585	1,020	3,011	1,920	1,065	624	1,238	833

Table A3. Appendix C. Tobit Estimation Results: Mortality Rate (MORT)

	Gender: Steer						Gender: Heifer			
	Placement: Fall/Winter			Placement: Spring/Summer			Placement: Fall/Winter		Placement: Spring/Summer	
Weight Class	600–700	700–800	800–900	600–700	700–800	800–900	600–700	700–800	600–700	700–800
Intercept	37.507***	41.577***	−0.017	23.497**	22.041***	8.809	34.412***	−14.096	39.978***	25.642*
	(1.355)	(1.142)	(1.943)	(1.652)	(1.028)	(1.708)	(1.405)	(2.467)	(1.207)	(1.999)
HRS	1.549*	1.799***	0.838	2.159***	−0.110	0.196	2.155**	−0.290	−0.201	−0.137
	(0.099)	(0.069)	(0.106)	(0.131)	(0.100)	(0.213)	(0.099)	(0.166)	(0.138)	(0.261)
HRS^2	−1.514**	−1.322***	−0.698	−1.863*	0.834	1.156	−1.964**	0.758	0.833	1.670
	(0.092)	(0.067)	(0.101)	(0.151)	(0.172)	(0.545)	(0.095)	(0.160)	(0.214)	(0.710)
HRS^3	0.557**	0.400**	0.252	0.625*	−0.245	−1.048	0.671***	−0.275	−0.166	−1.660
	(0.031)	(0.023)	(0.035)	(0.057)	(0.095)	(0.439)	(0.033)	(0.056)	(0.102)	(0.611)
HRS^4	−0.063**	−0.040**	−0.028	−0.068	−0.001	0.221	−0.072**	0.029	−0.007	0.509
	(0.003)	(0.003)	(0.004)	(0.006)	(0.015)	(0.104)	(0.004)	(0.006)	(0.015)	(0.150)
Winter/Summer	−0.388**	−0.024	−0.255**	0.147	0.131*	0.104	0.247	0.273	−0.129	−0.021
	(0.019)	(0.014)	(0.021)	(0.022)	(0.012)	(0.016)	(0.021)	(0.032)	(0.016)	(0.021)
lWEIGHT	−6.343***	−7.153***	−0.567	−4.009**	−3.794***	−1.598	−5.771***	1.874	−6.141***	−4.084*
	(0.206)	(0.173)	(0.290)	(0.250)	(0.158)	(0.256)	(0.214)	(0.377)	(0.187)	(0.303)
Loc	−0.198	0.260**	0.232*	−0.176	0.168**	−0.036	0.213	−0.236	0.117	0.115
	(0.018)	(0.014)	(0.022)	(0.022)	(0.012)	(0.019)	(0.020)	(0.030)	(0.016)	(0.022)
Yr	0.042***	0.053***	0.035***	0.026**	0.029***	0.016	0.028	0.012	−0.002	0.011
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
R^2	0.116	0.095	0.067	0.076	0.043	0.011	0.070	0.050	0.068	0.037
RMSE	1.809	1.431	1.186	1.324	1.094	1.068	1.683	1.694	1.466	1.269
n	1,447	2,705	1,585	1,020	3,011	1,920	1,065	624	1,238	833