The impact of drought on U.S. hay prices

by

Cordon Michael Rowley

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Major Professor
Jennifer Ifft

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Abstract

The relationship between drought and hay prices has important implications for cattle producers and federal safety net programs. Cattle producers rely on forage through grazing pastureland or hay as a primary feed source. Climate change and increasing extreme weather events, including more widespread and persistent drought, threaten the viability of livestock production in several areas of the US. When drought reduces hay production, producers typically decrease their herd size to manage low hay supplies or higher hay prices. Several safety net programs make payouts designed to cover forage losses caused by lower-than-normal precipitation or extreme drought conditions. However, these programs may be less effective if hay prices are dramatically higher when payouts are made or if payouts are not strongly correlated with forage losses. While the relationship between hay prices and drought has been studied in Germany, contemporary research conducted with US data is limited. In this study, we analyze the relationship between monthly drought conditions and hay prices, at both the state and district (sub-state) levels. In addition to quantifying this relationship, we also explore whether the relationship between drought and hay prices has changed over time and space and the impact of local versus widespread drought.

Methods

We first use state-level monthly hay prices reported by USDA NASS, which is available from 1950 to present for alfalfa hay and from 1972 to present for non-alfalfa hay. We then regress monthly hay prices against drought levels, measured by Palmer Drought Severity Index (PDSI) and Drought Severity and Coverage Index (DSCI), with fixed effects for state, month, and year. Second, we conducted a novel exploratory analysis using hay prices reported at the district level from the USDA Agricultural Marketing Service (AMS), for 3 states. USDA AMS

reports historic hay prices for districts within some U.S. states. We average county-level drought data at the AMS district level, with robustness checks for weighting based on cattle and hay production. We estimate a similar regression to our state-level model, and then extend it to include both district-level drought and state-level drought information. This allows us to consider whether regional market integration may mitigate the impact of local droughts. While drought conditions are arguably an exogenous shock to hay markets, our estimates are net effects of drought on hay price, that reflect how broad supply and demand factors respond to drought conditions. These factors, such as cattle inventories and local processing capacity, are excluded from our model due to simultaneity concerns.

Results

Using state-level data, we found that as both PDSI and DSCI increase, or drought becomes more severe, hay prices increase. Further, as drought becomes increasingly severe, the impact of drought on hay prices becomes greater. Mild drought conditions only have a small impact on hay prices, which could be due to production or management factors. These results are consistent when using growing-season precipitation instead of drought. For the district level, findings are consistent with state level analysis. Our results indicate the hay prices are not only strongly influenced by local drought, but also drought in proximate districts or states. The degree to which these effects are caused by hay markets, cattle inventories, or other market dynamics is an important topic for future research.

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Chapter 1 - Introduction

Water is a necessity of all life. When sources of water are limited by ecological factors, cattle producers are at the mercy of mother nature. This is why cattle producers can benefit from all available resources in analyzing and predicting adverse ecological effects on their operation. With drought conditions becoming ever more prevalent (Bates, 2021), we look to provide vital resources to cattle producers facing drought and inform federal safety net programs for forage producers. Cattle producers rely on dry forage in times when natural forage is insufficient (Boyer et al., 2019). Forage, as define by Oxford languages, is “bulky food such as grass or hay for horses and cattle; fodder.” We define dry forage as hay or dead grasses stored for cattle consumption and natural forage as grasses and other living organic matter that have not been harvested for cattle consumption. Producers store and feed hay when it is necessary to feed their herds. Producers are facing decreasing forage production more frequently as our climate changes (EPA, 2023) and presents new problems. Longer and more severe droughts are plaguing the American west (Bates, 2021), which constantly threatens producer livelihoods. This forces producers to choose between culling- the departure of cows from the herd due to sale, slaughter, or death- to maintain the rest of the herd or purchasing (potentially) expensive forage when their own forage supply is limited (Richards et al., 2017). There are several federal safety net programs available to provide relief to these producers. These programs provide financial aid and are not intended to cover the entire increase in costs that may results from adverse weather.

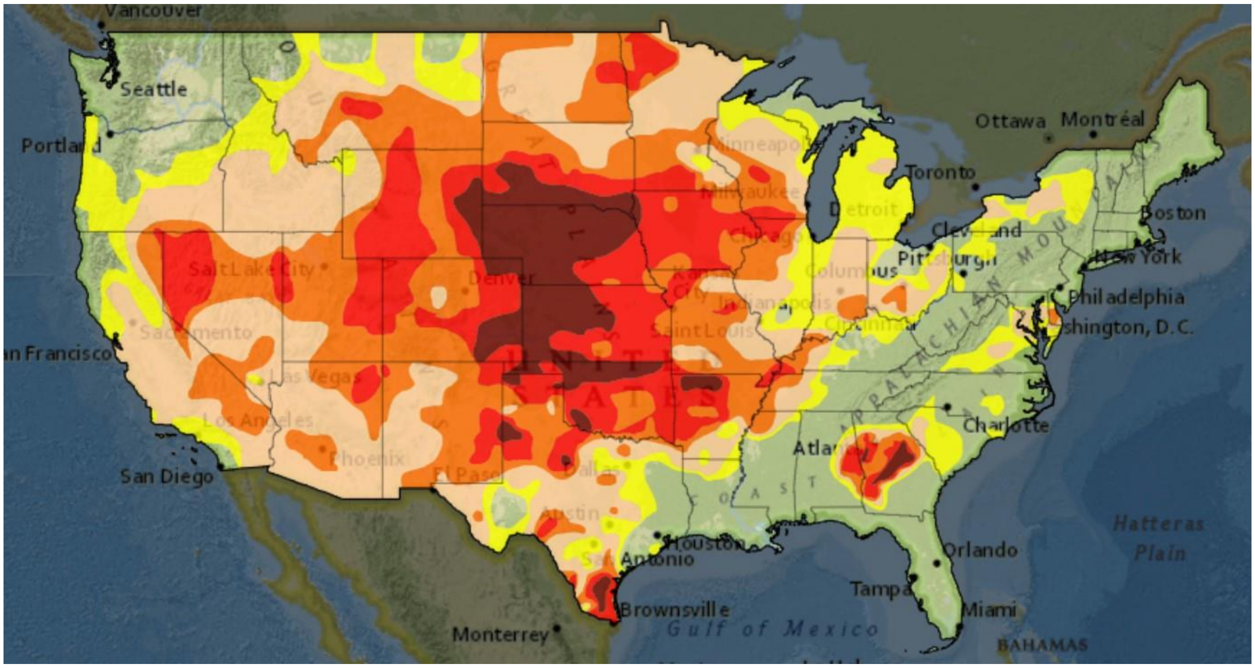
There are many anecdotes that when rainfall decreases, hay prices increase, and hay yields and production decrease (Cohen et al., 2020, Fu et al., 2021, Holupchinski et al., Ray, 2019). This led us to investigate the effect of drought on hay markets. Specifically, we will be conducting a state-level analysis investigating the magnitude of droughts’ effect on hay prices and how different levels of drought are reflected in these prices. We hypothesize that as drought increases, hay prices will increase, or that there is a positive relationship between our drought variables and hay prices. Given that our drought variable is cumulative, we plan to also regress discrete variables which correspond to levels reported by the U.S drought monitor. From "possible impacts", as reported by the U.S drought monitor, we know that impact of different degrees of drought affect plant life differently, or the impacts of drought are non-linear (U.S Drought Monitor). Essentially, the impact per category is expected to change and this model will capture those changes. Once performed, we expect the average effect of drought on hay price to increase as the drought categories increase. It is also important to note that we are measuring the net impact of drought on hay prices. Drought can reduce hay yields and thus reduce hay supplies and increase hay prices. However, drought can also lead to decreases on-farm hay storage/inventories and cattle inventories, which influence and potentially decrease the demand for hay. These common management practices are likely to mitigate the impact of drought on hay prices.

Upon reviewing the available literature, we found that there is limited state level analysis of hay markets and drought. In addition to limited research on the state level, there has never been a sub-state analysis of hay market and drought. This is concerning, as almost all federal safety net programs are based on a county level. This pushed us to perform not only a state analysis but a sub-state analysis as well. To perform such an analysis, we investigate the effects of drought on district-level hay prices using drought recorded in those districts. Districts are sections of a state comprised of several counties. These smaller regions may experience drought differently, as drought conditions are commonly not consistent across a state. We use the same empirical approach as at the state level, which is the interaction between drought and hay and how the average recorded hay price is affected for each level of drought recorded by the U.S drought monitor. Again, we suspect there is a direct positive relationship between drought and hay prices and that when drought severity increases hay prices increase substantially. We will then utilize interaction terms to compare district and state drought, we hypothesize that the magnitude of the effect will be less than recorded in the state analysis. We reached such hypothesis as there is local trade between producers in hay markets and we suspect when one region is experiencing drought another region not experiencing drought might trade with the other region.

This study allows the reader to understand impact of the magnitude of severe and persistent drought in U.S. states on hay markets. We utilized a drought variable in this study over precipitation and temperature variables, as drought is a cumulative measure that we believe has a stronger relevance for hay markets. Our contribution is an in-depth analysis at the state level, which will inform future research. Coupled with our state analysis, we provide an exploratory sub-state hay market drought analysis. Understanding the impact of drought at the district level will aid in studying how effective federal safety net programs are at aiding producers in times of drought. Compared to analysis of more aggregated data, this granular analysis will allow us to gather a deeper grasp of how local markets are affected by localized drought.

The following paper will be organized as follows. Chapter 2 will cover available literature and their findings. Chapter 3 will discuss the data utilized and their sources. Chapter 4 is where we explain and present our empirical models utilized for this study. Chapter 5 presents the findings from our research and discusses the results. Chapter 8 our findings summarized and our concluding thoughts on the data. Followed by references utilized in this paper, then succeed with an appendix with visuals for the reader.

Figure 1.1: Drought across the U.S, October 2012



Notes: The darker the coloring the more severe the drought conditions in the affected area
Source: Drought.gov, National Integrated Drought Information System

Chapter 2 - Literature Review

Most cattle operations in the U.S. are subject to seasonal weather cycles, which must be taken into consideration when developing a range management strategy (Reeves et al., 2015). A major component in all range management is developing a plan for feeding cattle when grasses die off (Reeves et al., 2015). Most beef producers select to feed hay in the winter to maintain their herds (Felix, 2023). Feeding cattle in the wintertime is the largest cost for cattle producers, which expresses the importance of proper feeding (Meteer, 2023). Hay is simply defined as "Grass mowed and dried for fodder" (Oxford Languages). The process of which hay is grown details managing land in which grass varieties can grow unrestricted to a substantial size. Then when the grass has reached a sustainable size producers' swath or "cut" the grass so that it falls to the ground (Woodmansee, 2022). Next, the fallen grass is raked several times for the moisture content to be released. After a period of raking and drying out in the sun, the grass is then raked into rows for which a bailor can be driven over, collected, and compacted into bales (Woodmansee, 2022). This step is crucial in the life cycle of hay, as baling at the right time is necessary to capture the right moisture content (Woodmansee, 2022). If the moisture content is too high, then when these bales are stored, there is a possibility of fires occurring (Woodmansee, 2022). Hay bales with a high moisture content may catch on fire due to a chemical reaction that occurs inside the bales. Chemical reactions may become more volatile when multiple bales are stacked upon one another (Schroeder, 2011). If the hay becomes too dry, then producers risk losing the hay's nutritional value (Laurenzi, 2019).

Cattle producers tend to feed hay to cattle, as hay is a good hedge against times when natural forage availability is low (Fitzgerald, 2018). Hay normally is a more cost-effective source of energy (Cooke, 2023) compared to alternatives such as corn, oats, and barley. The major advantage to feeding grains to cattle is a higher nutrient content (Dhuyvetter, 2021). Though this can be counterbalanced, in most instances, cattle producers supplement these nutritional differences with a salt lick, protein tubs, and powder additives that cattle would have access to (Larson, 2022). As for current management strategies, the best financial decision is heavily reliant on the price of hay relative to the price of grains (Felix, 2023).

Given how vital hay is to most cattle operations, studying how drought impacts hay prices is critical. The impact of drought on yields and production has been studied several times (Cohen et al., 2020, Fu et al., 2021, Holupchinski et al., Ray, 2019). When rainfall is inadequate, major grains and hay production is reduced. This causes less supply in the market and over time, these prices increase. The magnitude of the effect is heavily influenced by the degrees and persistence of drought. Literature investigating the magnitude of drought on hay markets is limited, with most current studies being performed outside the U.S. One such article written by (Schaub & Finger, 2020) found that drought at the regional level created a substantial increase in hay prices (15%) in South Germany. For the U.S., we find limited research investigating the U.S. hay markets and the magnitude of the effect of drought (Bauman, 2014). For example, Bauman (2014) estimated the economic impact of drought on the economy in southern Colorado losses of over $5 million for effected hay markets in the 17 counties reviewed. Studies forecasting hay prices were reviewed to better understand factors that affect hay markets. (Blake & Clevenger, 1984). Blake and Clevenger (1984) wrote of annual and monthly models forecasting alfalfa prices in New Mexico. They utilized aspects of hay acreage current and previous, hay production as a function of hay acreage, and price-dependent demand when forecasting alfalfa prices.

Generally, relatively few studies explicitly document the empirical estimates of hay acreage or production elasticity to prices (e.g., Shumway 1983; Knapp and Konyar 1991; Bazen et al. 2008). These studies focus on the perennial nature of hay crops and utilize dynamic or time-series models to estimate the supply responses. Most US studies on hay prices are older and focus on forecasting or quality characteristics, not inventories or weather. In addition to Blake and Clevenger (1984), some studies have considered the relationship between hay prices and hay quality: Pardew (1988) used survey data from Nebraska and (Rudstrom 2004) used auction data from Minnesota. Blake and Catlett (1984) analyzed the potential for cross-hedging hay using corn futures. Skaggs and Snyder (1992) compared different forecasting methods for California alfalfa hay prices.

A key component of our research is to understand where most of the consumption of hay is in the U.S. markets. From our research, we have identified cattle—cow-calf, dairy, and beef-operations—as a major source of demand. Therefore, to formulate research with a greater impact we utilized the research of Jarvis (1974) and Rosen et al. (1998) to gain a better grasp of the U.S. cattle cycle. Both Jarvis and Rosen equate cattle as a capital good, therefore the value of a cow in production will be maintained until the value of slaughter exceeds that of production. If feeding cattle expensive hay causes the value of production to decrease, then producers would sell their cattle. When understanding the cattle cycle, it is also important to acknowledge that cattle inventory themselves is influenced by drought. This impact of drought on cattle herds has been studied by Skidmore et al. (2022) and Patalee & Tonsor (2021). Skidmore et al. (2022) investigated the impacts that drought had on Brazilian cattle inventories. They found in times of drought producers opted to sell cattle instead of buying hay from the market when prices are high. Patalee & Tonsor (2021) analyze how sensitive the beef industry is to weather and how more weather information can lead to better risk management for U.S. beef producers.

Information on drought and cattle and forage market dynamics is useful for producers managing herd size in drought, as well policymakers and supply chain participants.

Chapter 3 - Data and Data Descriptives

State Hay Price

We utilized USDA NASS hay price data for alfalfa 1950 to 2022 and non-alfalfa 1972 to 2022 (Table A.1). The values recorded represent price per ton. USDA NASS was able to collect and estimate these hay prices from surveys of dealers, hay auctions, and other buyers such as dairies or cattle feeders (USDA). This hay price sample was chosen for its availability and completeness for the target years. The selected recording was an average monthly price for all states. We selected 27 states based on consistent hay price recording. To manage the impact of missing data, if a state's hay price data was missing a cumulative 3 decades of hay prices, the state was omitted from the analysis (Table A.2). Most states omitted from this analysis also lacked significant cattle inventories and hay production, relative to the selected states.

State Weather Variables

Palmer Drought Severity Index (PDSI)

Our first drought variable utilized for the state study is Palmer Drought Severity Index or PDSI (Table A.3). PDSI data was collected from the National Oceanic and Atmospheric Administration or NOAA. PDSI uses available temperature and precipitation data to estimate the relative dryness of a region (NCAR). The strengths of PDSI are in its abilities to determine long term drought at all levels of severity and the use of physical water balances (NCAR). Weaknesses of PDSI are found in comparing values across regions and lack of accounting for snow and ice (NCAR). The data utilized for this study was monthly values of PDSI per state selected in this sample. When using monthly PDSI, it is important to note that the drought values recorded are cumulative and account for previous conditions up to a year in time. The standardized scale of PDSI is -10 (worst degrees of drought) to 10 (the wettest possible measure). Most recordings of PDSI are on a scale of -4 to 4, with values outside of this range considered extreme outliers. In this analysis we are investigating the net effect of drought on hay prices, therefore the data represents a dryness of 0 normal conditions or no drought to -4 exceptional region drought (Table 3.1). The time of data collection matches the time series of hay prices, 1950 to 2022 and 1972 to 2022. We find drought measures more impactful to hay markets compared to aggregated precipitation. This is largely estimated as drought measures account for various factors such as physical water balances and cumulative environmental effects.

Table 3.1: PDSI and U.S Drought Monitor Categories

PDSI	**U.S Drought Monitor Categories**
-1- -1.9	Abnormally Dry Conditions
-2 - -2.9	Moderate Drought Conditions
-3 - -3.9	Severe Drought Conditions
-4 - -4.9	Extreme Drought Conditions
-5 or lower	Exceptional Drought Conditions

Drought Severity and Coverage Index (DSCI)

An additional drought measures used in conducting this research was Drought Severity and Coverage Index or DSCI for the U.S. Drought Monitor (Figure A.4). DSCI is an experimental method of converting drought levels into a single value for an area (U.S Drought Monitor). The U.S. drought monitor reports droughts intensity in five categories exceptional, extreme, severe, moderate, and abnormally dry. To gauge this range of severity, U.S drought monitor utilizes "the Palmer Drought Severity Index, the Standardized Precipitation Index, and other climatological inputs; the Keech-Byram Drought Index for fire, satellite-based assessments of vegetation health, and various indicators of soil moisture; and hydrologic data, particularly in the West, such as the Surface Water Supply Index and snowpack" (U.S drought monitor) along with experts and local observers in the climate industry. They then use a weighted sum of drought by region to summarize the severity of drought into a numerical scale, 0 (no drought) to 500 (100% of the region is in exception drought). We can then utilize this scale (Table 3.2) to regress against hay prices for a specific region to conduct this analysis. For this analysis we used DSCI recorded monthly per state from 2000 to 2022. DSCI, being a comparatively new drought measure, only has data available from present until the year 2000. The benefit of DSCI as compared to PDSI is DSCI is available at the county level where PDSI is not. This in return should have a better predictive ability for localized droughts. Times series for hay prices was adjusted to meet the constraint of the reporting period.

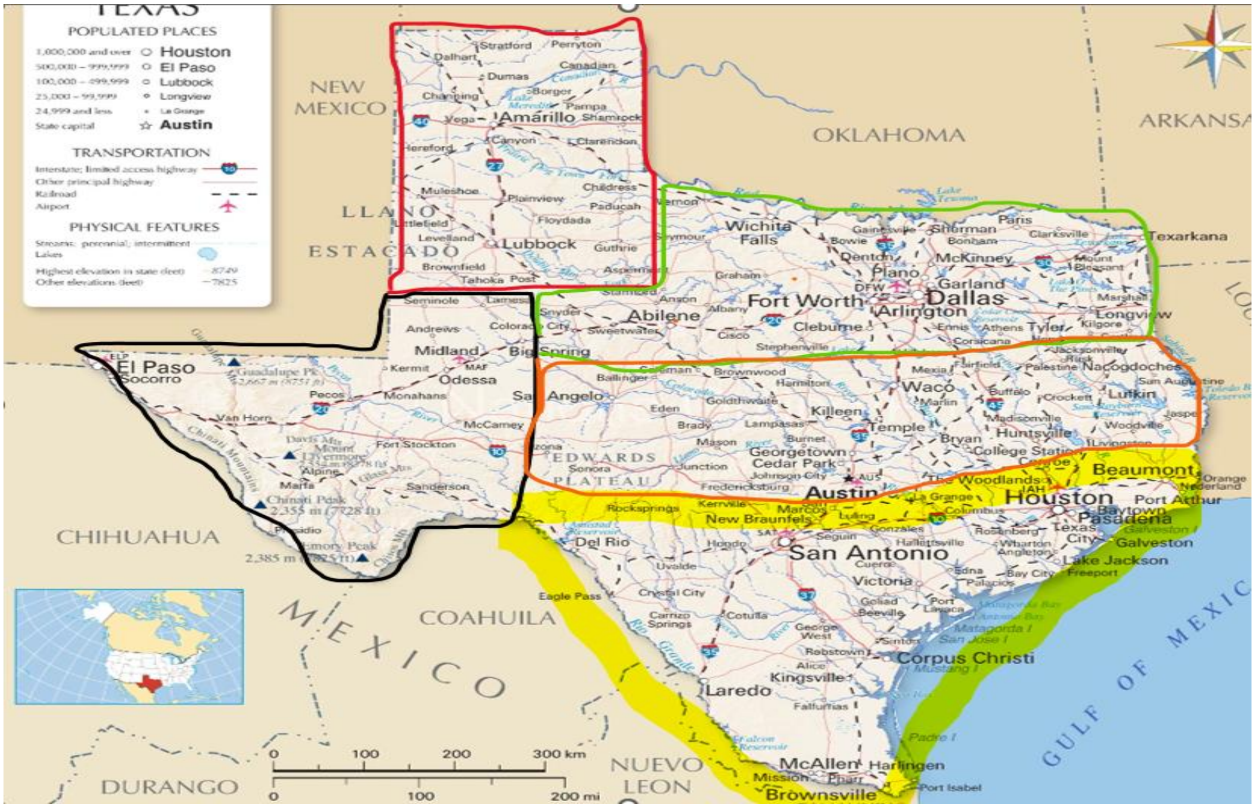
Precipitation

As a robustness check for our drought measures, we also utilized precipitation data collected by NOAA (Figure A.4). This data was collected utilizing rain gauges from weather stations and satellite imaging. The data for this study was recorded monthly for their respective state from 2000 to 2022. The value recorded was aggregate inches per state per month. Precipitation is vital to hay and, generally, crop production. Declines in production due to lower precipitation decrease supply and increase prices. We elected to use precipitation as a robustness check against the potentially subjective aspects of PDSI and DSCI. We account for monthly precipitation levels, as well as precipitation during typical growing season months in our empirical model.

District Hay Price

For our district hay prices we used USDA AMS data for alfalfa and grass hay prices for the selected districts in their respective states. District data is only reported for 15 states. This data was recorded monthly from each district and the publicly available timeframe per each district ranged from 2000 to 2020. The value recorded varies from state to state, with two styles of reported hay prices: simple and weighted reporting. Simple recordings define hay types into alfalfa and grass hay, while weighted reporting account for specific hay type such as alfalfa, alfalfa mixes, bluestem grasses, brome grasses etc. For our district analysis, we choose the districts of Colorado, Texas, and Kansas (Table A.5, Table A.6, Table A.7). Texas and Colorado recorded simple hay prices. For consistency, Kansas weighted hay price data was categorized into alfalfa and grasses. We assigned an indicator for grass types and alfalfa types and calculated the average price by grass and hay for all varieties reported within a month. These states were selected based on availability of data; if a state's district recording was missing a cumulative 5 years of data, the data was not a district, or a partial representation of the state. (Table A.8, Table A.9). This data was gathered from a report by a state hay analyst who oversees recording transactions in each respective district. Data was selected for the availability of district hay prices, which at this time is the only publicly available source. The USDA AMS does not record using the typical agricultural or weather districts (Figure 3.1). Given this mismatch, we aggregated county level weather variables using a simple average as well as robustness checks with county averages weighted by cattle inventories and hay production.

Figure 3.1: Texas District Mapping



Notes: The multiple color lines indicated different reported hay districts
Source: USDA Agricultural Marketing Service

District Weather Variables

DSCI

Given the distinct recording for hay prices by the USDA AMS, we needed to utilize county level data to aggregate to these districts. PDSI is not recorded for the counties of U.S. states, therefore we could not utilize this measure for our district analysis. DSCI as outlined previously was one of the only droughts measures, we could utilize for this study. The DSCI utilized for the districts follows the same recording and scale as the state DSCI (Table 3.2, Table A.5, Table A.6, Table A.7). DSCI at the county level was also selected over drought measures such as SPI and SPEI, as we find it is vital to account for physical water balance when investigating the hay markets in the U.S. (U.S. Drought Monitor).

Table 3.2: DSCI and U.S Drought Monitor Scale

DSCI	U.S Drought Monitor Categories
0-100	Abnormally Dry Conditions
101-200	Moderate Drought Conditions
201-300	Severe Drought Conditions
301-400	Extreme Drought Conditions
401-500	Exceptional Drought Conditions

Cattle Inventories

When studying the effects of drought on hay markets, it is important to acknowledge cattle inventories as cattle are a major source of demand for hay. As a part of our state analysis, we collected milk cow inventories and beef cow inventories for the time corresponding to our analysis of alfalfa hay prices, grass hay prices and DSCI (1950 – 2022), (1972-2022), and (2000-2022). All cattle inventories were sourced from USDA NASS Quick Stats data. This data was collected via surveys administered to cattle operation in the U.S. For our analysis, we recorded the annual milk and beef cow inventories per state.

For our district analysis, because we needed to aggregate our drought measure, we used the recorded cattle inventories per county of each state as a robustness check. To account for variance in demand between the counties hay prices, we weighted DSCI at the county level by cow inventory. We choose specifically the cow inventory as this is a consistent gauge for the magnitude of cattle in the U.S. Calves and bulls are important to take into consideration, but cattle operation require the cows to function.

Irrigation Data

We wanted to account for additional sources of water and how it affects hay market dynamics. Therefore, in our state analysis we utilized acres harvested that have been irrigated. This data was collected via census data from the USDA NASS Quick Stats. The time value of the data recorded for alfalfa hay prices and grass hay prices follows (1997, 2002, 2007, 2012, 2017), and (2017). Not all states display a significant amount of irrigated hay pastures. In response, we also recorded acres harvest for each state to create a percentage of harvested acres irrigated for our analysis.

Chapter 4 - Empirical Framework

Stationarity Test

Since this is a times series analysis it is important to test if the values are stationary or non-stationary. A data set is considered stationary when the statistical properties for mean, variance, covariance, and standard deviation do not vary over time, with non-stationary being the opposite. To test the stationarity of the data utilized in the state model we conducted a unit root fisher test with the option of dicky fuller, a Dicky-Fuller test, investigates the null hypothesis at a unit root in an autoregressive time series model. Our null hypothesis for this test was the data being non-stationary. When conducting this test, we accounted for time and space, using a state id number and time (year and month data). Upon conducting this analysis for the state-level data series, we found with statistical confidence we can reject the null (Figure A.1, Figure A.2, Figure A.3). In other words, the data in the state analysis, PDSI, DSCI, and hay price are generally stationary. Therefore, we may continue with a standard OLS regression.

To test the district data, which is especially important given that this data has not been previously used for hay market analysis (to the best of our knowledge), we used a unit root fisher test with the option of dicky fuller. Again, our null hypothesis being non-stationarity. From our testing we found that the grass hay markets for the districts of Colorado and Texas and the alfalfa markets for the districts of Kansas were non-stationary (Figure A.4 Figure A.5 Figure A.6). All other markets and districts were found stationery. To counteract this effect, we then took the difference between price, DSCI. After retesting the difference, we found the differenced data to be stationary, therefore we could then continue in our OLS regression. The issue of such adjustments will limit our interpretation at the district level to trends.

Empirical Specification: State-level Analysis

To investigate the magnitude of drought impacts on hay market prices we regressed recorded alfalfa and grass hay prices from the USDA NASS against our weather variables, PDSI, DSCI and precipitation. We will be utilizing ordinary least squares regression for state-level analysis. This model is shown below.

$$(1) \quad P_{tsym} = D_{sym} + S + Y + M + \epsilon_{tsym}$$

P_{tsym} – Price for grass or alfalfa type hay (t) for each state per year per month

D_{sym}- PDSI or DSCI for each state per year per month

S – State fixed effect

Y- Year fixed effect

M- Month fixed effect

ϵ_{tsym}- Error term for each type, state, year, month observation

This regression will show how a one-unit increase in our weather variables will affect the price per ton of recorded hay transactions. Given the data is recorded over time and multiple states, we added fixed effects for state, year, and month. This is necessary when using a cumulative drought variable, as drought and its magnitude changes from year to year and region to region. Market conditions can also vary over space and time. These fixed effects allow us to accurately gauge droughts' impact as it controls for these time and location-fixed factors. From this regression, we can test out the hypothesis of the effect of drought increases on hay prices. Our first hypothesis will be displayed by the coefficient associated with drought variables. Based on the positivity or negativity of that coefficient we can determine the relationship between the two.

For our second state regression, we wanted to specially target the degrees of drought and their magnitude. From the scale outlined in our data section, we created discrete values for our drought variables and regressed against state hay prices. Abnormally dry conditions and no drought were omitted as we are specifically interested in the effect of drought.

$$(2) \quad P_{tsym} = D_e + D_{ex} + D_s + D_m + S + Y + M + \epsilon_{tsym}$$

P_{sym} – Price by type, for each state per year per month

D_e- Exceptional Drought

D_{ex}- Extreme Drought

D_s- Severe Drought

D_m- Moderate Drought

S – State fixed effect

Y- Year fixed effect

M- Month fixed effect

ϵ_{sym}- Error term for each type, by state, year, and month

This regression will show how on average the price per ton of hay changes once a state has a significant percentage coverage for each level of drought severity. These coefficients are vital to displaying how as the droughty severity changes hay price increase. As with our continuous regression, given the data is recorded over time and multiple states, we added fixed effects for state, year, and month. From this regression, we can assess our hypothesis, as drought persists and increases the price of hay should significantly increase given various degrees of drought.

As an extension to this analysis, we also want to account for cattle inventories and irrigated acres harvested. Upon calculating inventories and percentage of acres irrigated, we then divided our sample into two parts based on the median amount per state, averaged over the entire study period. Irrigation and inventory levels may be jointly or simultaneously determined with drought and hay prices, which is we spilt our sample instead of incorporating these variables.

Empirical Specification: District-level Analysis

For our district analysis, we used a similar regression to the state analysis shown below (1). However, we need to difference the current and previous data for certain types of hay markets for certain districts identified to have nonstationary data. In differentiating our data, we removed variation to counteract the non-stationarity. As a robustness check for DSCI, we ran the same model weighting for county cattle inventories and county hay production (5)(6) instead of a simple average.

$$P_{tdsym} = D_{dsym} + S + D + Y + M + \epsilon_{tsym} \tag{3}$$

$$\Delta P_{tdsym} = \Delta D_{dsym} + S + Y + M + \epsilon_{tsym} \tag{4}$$

$$P_{tdsym} = DCOW_{dsym} + S + D + Y + M + \epsilon_{tsym} \tag{5}$$

$$P_{tdsym} = DHAY_{dsym} + S + D + Y + M + \epsilon_{tsym} \tag{6}$$

P_{tsym} – Price by hay type, for each district in state per year per month

D_{sym}- DSCI record for each district in state per year per month

ΔP_{sym}- Differenced price per district per state

ΔD_{sym}- Differenced DSCI per district per state

$DCOW_{sym}$- Weighted DSCI per cattle inventory

$DCOW_{sym}$- Weighted DSCI per hay production

S – State fixed effect

D- District fixed effect

Y- Year fixed effect

M- Month fixed effect

$\in_{tsym}$- Error term for each type, by state per year per month

This regression model will show how a one-unit increase in DSCI will affect the price per ton of recorded hay transactions. Given the data is recorded over time and multiple states, we added fixed effects for state, district, year, and month. These fixed effects allow us to accurately gauge droughts' impact, as it assigns a time and place. From this regression, we can test out the hypothesis of droughts increases hay prices increase but on a district level. Our first hypothesis will be displayed by the coefficient associated with drought variables.

For our second district regression, we wanted to specially target the degrees of drought and their magnitude. We again converted DSCI into discreet variables in the ranges of drought that DSCI equates to. This range was outlined in the data and data description section. We also weighed such analysis by county cow inventory and county hay production with the discreet variables created the regression follows as such.

$$(7) \quad P_{tsdym} = D_e + D_{ex} + D_s + D_m + D + S + Y + M + \in_{tsdym}$$

P_{tsdym} – Price record per transaction, for each type, district in the state per year per month

D_e- Exceptional Drought

D_{ex}- Extreme Drought

D_s- Severe Drought

D_m- Moderate Drought

S – State fixed effect

D - District effect

Y- Year fixed effect

M- Month fixed effect

ϵ_{tsdym}- Error term for each type, district in the state per year per month

This regression will show how on average the price of hay changes once a district has a significant percentage coverage of a certain drought severity. These coefficients are vital to understanding how hay prices are influenced as drought severity changes. As with our continuous regression, given the data is recorded over time and multiple states, we added fixed effects for district, state, year, and month. From this regression, we can see how as drought persists and increases, the price of hay should increase per degree of drought.

Interactions

A key part of this study is to compare droughts effect at the district level and the state level. We are interested to see how factors affecting the local hay market affect the increase in hay prices due to drought. To conduct this, we aggregated the scaling of drought at the district level and state level by splitting our drought categories into no to moderate drought (no to moderate drought) and severe to exceptional drought (extreme drought). We created the interactions as follows, with the omitted category being no district or state drought.

ESED- extreme state drought, extreme district drought

NMSED- No to moderate state drought, extreme district drought

NMDES – Extreme state drought, no to moderate district drought

These interactions were created utilizing levels of DSCI. DSCI less than 200 is no drought to moderate drought, with 201-500 for extreme drought conditions. From these interactions we can see the change in magnitude when drought is at extreme conditions for the district level as compared to the state.

For our state regression since we had data before 2000 to current, we also had a question about the effect that the renewable fuel standard had on hay prices after it was enacted in 2005. The renewable fuel standard required gasoline blends with renewable fuel such as ethanol. This action increased the demand for corn to be produced into ethanol. Corn is a major nutrient source of feed for cattle. Since the demand for corn was increased the prices would have become higher for producers. We know from literature that when corn prices increase, cattle producers would seek alternatives and subsequently feed more hay. Likewise, land could be converted to corn production from other activities. We are interested in this effect and therefore created an interaction with PDSI and the enactment of the renewable fuel standard.

Robustness checks and standard error estimation

Drought measures take into consideration many factors outside of rainfall (see chapter 3). To test if our assumption of drought being positively correlated with hay prices, we must test another weather variable. We selected precipitation to test our null hypothesis. If our variable for drought has a positive relationship with hay prices, then precipitation should have a negative relationship. This is assumed because rainfall quantity is necessary to production of hay, lack of production would increase hay prices.

To correct for potential correlation over time and season in standard errors, we clustered all standard errors by year and month. Weather and prices are likely correlated over space. However, the number of districts and states is relatively small, which can create a downward bias if standard errors are clustered (Cameron and Miller, 2015). Given that our data is at a large geographic scale, either by state or districts which include several counties, we thus do not adjust standard errors for spatial correlation.

Chapter 5 - Results and Discussion

State-level Analysis

The regressions as shown in table 5.1 display the impact of PDSI on alfalfa and non-alfalfa hay prices for the states utilized in this study.

Table 5.1: PDSI and State Hay Price, 1950-2022

VARIABLES	(1) Alfalfa Price per ton	(1) Non-Alfalfa Price per ton
PDSI	-1.830***	-1.633***
	(0.0979)	(0.0982)
Constant	293.7***	211.5***
	(2.671)	(2.161)
Observations	21,559	16,447
R-squared	0.735	0.725

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

The first notable result of this regression is the relationship between PDSI and hay prices. For all types of hay, we see a negative relationship. For a one unit decrease in PDSI, or an increase in drought, we find that hay prices increase. This matches and confirms our first hypothesis, as drought increases hay prices increase. From this regression we see that per unit of PDSI hay prices per ton increased $1.63 - $1.83 dollars in value. While we do not test for statistical differences, the estimated PDSI coefficient for alfalfa price is larger than for non-alfalfa. This is consistent with more inelastic demand for alfalfa hay. This increase and difference are also backed by the regressions in table 5.2. The following table 4 displays the discrete impact of drought on state hay markets, by capturing the categories of drought by the U.S drought monitor.

Table 5.2: Discrete PDSI and State Hay Prices, 1950-2022

VARIABLES	(2) Alfalfa Price per ton	(2) Non-Alfalfa Price per ton
Exceptional	27.43***	24.48***
	(1.626)	(1.735)
Extreme	16.51***	9.631***
	(1.323)	(1.370)
Severe	13.72***	5.336***
	(1.033)	(1.063)
Moderate	6.490***	5.836***
	(0.843)	(0.876)
Constant	292.2***	210.1***
	(2.674)	(2.180)
Observations	21,559	16,447
R-squared	0.734	0.722

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

Foremost from this regression, there is a significant increase in hay prices per category of drought. This confirms our second hypothesis, as drought increases in severity the impact on hay prices also increases. When comparing state alfalfa markets to non-alfalfa markets, the relationship between drought and price for alfalfa is consistently higher than the non-alfalfa. Between coefficients from the discrete analysis, we conducted a t-test for statistical differences between the coefficients. We found that the only coefficients with no statistical difference to be the moderate and severe drought conditions in the state grass regression.

Next, we display the impact of drought on U.S hay markets, this time utilizing DSCI as our drought variable. This regression is from 2000 to 2022, as this is the only available time recorded for DSCI. PDSI has potential weakness as discussed in the Data chapter, to confirm our results in the PDSI analysis we wanted to also use another drought measure. From table 5.3, we see a positive relationship between DSCI and hay price for all states, and hay type, this is consistent with our analysis of PDSI. As drought increases, hay prices increase.

Table 5.3: DSCI and State Hay Prices, 2000-2020

VARIABLES	(1) Alfalfa Price per ton	(1) Non-Alfalfa Price per ton
DSCI	0.0807***	0.0572***
	(0.00369)	(0.00431)
Constant	148.9***	152.9***
	(2.555)	(2.400)
Observations	7,452	7,451
R-squared	0.754	0.784

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

We see that per unit increase in DSCI that hay prices increase. The advantage of DSCI is that DSCI represents a 1 percent increase in drought area coverage per degree of drought. Therefore, from these results we see that on average per 1 percent increase in area of drought that hay price increase from range of 5 cents a ton to 9 cents a ton. While this may allude to a minor impact, if DSCI were to increase to the entire area being 100% effected by drought then the increase in price per ton would signify a $3 dollar increase to a $9 dollar increase, which has significant impacts to the financial feasibility of these operation. Again, alfalfa markets display a larger response to drought than non-alfalfa hay markets.

In table 5.4 we display the discrete evaluation with DSCI for each category of drought. Again, we see that the impact of drought on hay prices increases with each category of drought matching our PDSI analysis and confirming our second hypothesis.

Table 5.4: Discrete DSCI and State Hay Prices, 2000-2022

VARIABLES	(2) Alfalfa Price per ton	(2) Non-Alfalfa Price per ton
Exceptional	34.34***	20.58***
	(4.040)	(2.657)

Extreme	27.14***	21.92***
	(2.312)	(1.742)
Severe	14.25***	9.789***
	(1.293)	(1.202)
Moderate	5.172***	3.745***
	(0.934)	(0.858)
Constant	153.7***	156.3***
	(3.284)	(2.341)
Observations	7,452	7,451
R-squared	0.753	0.784

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** $p<0.01$, ** $p<0.05$, * $p<0.1$

With this analysis, we see that when comparing the alfalfa markets to non-alfalfa markets the impact of drought is higher. While we do not formally test for differences, this is consistent with our PDSI analysis of producers purchasing alfalfa hay are less price sensitive compared to producers purchasing non-alfalfa hay. Again, this is price transaction data, the impact of hay prices only shows sold hay. All coefficients were tested for equality with the corresponding nearby drought measure and found to be statistically different.

As a robustness check to our drought variables, we regress precipitation and precipitation in the growing season against state alfalfa price and state non-alfalfa prices. We define the key growing season for hay in the U.S. as May to October. Table 5.5 shows that precipitation is negatively correlated with hay prices. This result corresponds with our assumption that hay prices increase when precipitation decreases. The precipitation variable we used is an aggregate monthly representation of rainfall in inches. When looking at the overall impact of precipitation we see that the results were not statistically significant. When interacted with the growing season of hay, we see that the coefficient becomes significant and increases in magnitude. This is an expected result as rainfall during the growing period is vital to hay production.

Table 5.5: Precipitation and State Hay Prices, 2000-2020

VARIABLES	(1) Alfalfa Price per ton	(1) Non-Alfalfa Price per ton
Precip	-0.0848	-0.257
	(0.339)	(0.298)
GS*Precip	-0.987**	-0.900**
	(0.426)	(0.375)
Constant	160.3***	160.8***
	(2.609)	(2.293)
Observations	7,452	7,452
R-squared	0.738	0.776

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

Drought is not always the same across regions, therefore producers in areas affected by drought may seek hay from areas experiencing non-drought conditions to feed their cattle. To investigate this, we took the average drought for all the bordering states and matched that average to the state in the model. Based on the drought in the surrounding state, we should see an impact to state hay prices. In table 5.6, if a surrounding state is experiencing a degree of drought, then the impact is displayed greater than the states PDSI. Upon testing the difference of the coefficients between the PDSI variables for the alfalfa and non-alfalfa markets utilizing a t-test, we cannot confidently say the coefficients are truly different. Therefore, we cannot conclude that drought affecting the surrounding states has a significant impact on that states hay market.

Table 5.6: PDSI and Surrounding States, 1950-2022

VARIABLES	(1) Alfalfa Price per ton	(1) Non-Alfalfa Price per ton
PDSI	-1.332***	-0.749***
	(0.121)	(0.120)
PDSI-Border	-1.376***	-2.459***
	(0.195)	(0.194)
Constant	293.6***	211.8***
	(2.668)	(2.150)
Observations	21,397	16,285
R-squared	0.735	0.727

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

Cattle inventories, irrigation and other factors affecting the hay markets are captured in our error term for the previous model. To investigate the impacts of cattle inventories and irrigation we created a split model based on the ratio of milk cows to beef cows (Table A.10) and percentage of acres harvested that have been irrigated (Figure A.11). In table 5.7 we show how the states with a ratio greater than 50% and less than 50% of milk cows over beef cows. We therefore account for states with a strong dairy cow inventory and states with a higher beef cow inventory.

Table 5.7: Cattle Inventories Split Analysis, 1950-2022

VARIABLES	(1) Alfalfa Price per ton >50% Milk Cow	(1) Alfalfa Price per ton <50% Milk Cow	(1) Non-Alfalfa Price per ton >50% Milk Cows	(1) Non-Alfalfa Price per ton <50% Milk Cow
PDSI	-1.170***	-1.954***	-1.195***	-1.548***
	(0.209)	(0.155)	(0.232)	(0.139)
Observations	7,922	13,475	5,597	10,688
R-squared	0.686	0.787	0.658	0.782

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

We display that the impact of PDSI on the hay markets, that states with a larger average milk cow inventories are less impacted by drought. We cannot conclude that these magnitudes are different. This may be a case of limited observations for the regressed data or broader structural change in the dairy industry over our study period not being captured. More testing is necessary to understand how different cattle inventories and drought affect hay markets.

When thinking why drought affects hay prices, the first assumption is lack of available water for the hay crop when being produced. The main source of water for hay comes from rainfall, but rainfall is not the only source of water for some hay producers. Hay producers in the states of Colorado, Wyoming, and Montana (to name a few) heavily rely on irrigating hay for production. When assessing the impacts of drought, these producers may be less affected. Therefore, we utilized the same model, but this time we split the data into states with over 50% hay acres harvested irrigated and less than 50 percent irrigated (Table A.11). In table 5.8 we see that in hay markets that have a majority irrigation have lower drought sensitivity than markets that have lower irrigation.

Table 5.8: PDSI and Irrigation, 1950-2022

VARIABLES	(1) Alfalfa Price per ton >50% Irrigated	(1) Alfalfa Price per ton <50% Irrigated	(1) Non-Alfalfa Price per ton >50% Irrigated	(1) Non-Alfalfa Price per ton <50% Irrigated
PDSI	-0.888***	-2.342***	-1.390***	-1.479***
	(0.185)	(0.164)	(0.174)	(0.154)
Constant	284.6***	282.9***	214.0***	179.2***
	(3.851)	(3.331)	(3.345)	(2.606)
Observations	9,221	12,176	5,413	10,872
R-squared	0.759	0.738	0.722	0.711

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

When looking at the effects of PDSI and hay price for states with majority irrigation, there is a difference in the impact of drought. This is apparent when looking at the alfalfa markets. The impact is quite large when the alfalfa crop is not irrigated, but it is important to note that prices are still affected by drought. The effect in the non-alfalfa market is less of an overall impact and cannot be concluded that there is a difference, but this can be heavily attributed to the amount of grass hay that is irrigated. From analysis of the data there is significantly more alfalfa irrigated by state than non-alfalfa figure (Table A.11).

Finally, to conclude our state analysis, we investigate the impacts of the renewable fuel standard on hay prices in drought. In table 5.9 we see that for non-alfalfa hay, after the renewable fuel standard was enacted, the impact of drought on state hay prices increased.

Table 5.9: Renewable Fuel Standard and PDSI, 1950-2022

VARIABLES	(1) Alfalfa Price per ton	(1) Non-Alfalfa Price per ton
PDSI	-1.738***	-1.005***
	(0.169)	(0.155)
RFS*PDSI	-0.300	-1.616***
	(0.277)	(0.261)
Constant	293.6***	210.3***
	(2.726)	(2.819)
Observations	21,397	16,285
R-squared	0.735	0.726

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

In non-alfalfa markets, we see a higher degree of impact as compared to the aggregate PDSI impacts. We contribute to this magnitude of change in feed markets driven by the RFS as well as other market developments around the same time (Carter, Rausser, and Smith, 2017). Corn may be utilized as a substitute for hay when prices become too high. With the renewable fuel standard, the demand for corn increased and so did the prices of corn. Thus, in drought, producers were forced to pay higher prices for hay, as corn may have been more expensive. Originally, we estimated the factor of this change to the possibly of climate related changes resulting in higher frequencies of drought. Upon comparing PDSI from before 2005 and after 2005, we found drought levels were relatively similar before and after.

District-level Analysis

Following our state analysis, we then investigated the impact of drought on district hay prices utilizing similar modeling. First in table 5.10, we display the relationship between DSCI and district alfalfa and grass hay markets. This initial modeling is of the districts that were found to have stationary price and drought data series. From this regression, we find a positive relationship between DSCI and hay prices. This matches our state analysis.

Table 5.10: Stationary DSCI and District Hay Price, 2000-2020

VARIABLES	(3) CO District Alfalfa Price	(3) TX District Alfalfa Price	(3) KS District Grass Price
DSCI	0.0568***	0.0630***	-0.00440
	(0.0113)	(0.0175)	(0.00889)
Constant	114.3***	177.0***	68.18***
	(6.949)	(7.634)	(3.669)
Observations	1,019	698	610
R-squared	0.720	0.619	0.511

Note: Control variables for state, district, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

For the Colorado districts and Texas districts alfalfa markets, we see a ~6 cent increase in per ton per one unit increase in DSCI. This corresponds with the increase we saw in the state DSCI analysis. Again, this is a 1% increase in area coverage on average per drought degree. If a district were to experience 100% area coverage for any degree of drought, our results suggest the increase in price per ton to be $6 dollars. For the grass hay markets in the districts of Kansas we do not find a statistically significant impact of drought on hay prices. This is likely a result of our aggregation of weighted hay types to a simple representation of alfalfa and grass.

Next, in table 5.11, we see the discrete drought analysis for the stationary districts. While not as prominent compared to the state analysis, there is still a noticeable trend in the increase of impacts per degree of drought in these districts for all significant values. This is like our state analysis and again supports our hypothesis, as drought increases in severity over time, the impact increases as well.

Table 5.11: Discrete DSCI and District Hay Prices, 2000-2020

VARIABLES	(7) CO District Alfalfa Price	(7) TX District Alfalfa Price	(7) KS District Grass Price
Exceptional	19.38***	53.47***	-7.928**
	(5.091)	(9.715)	(3.843)
Extreme	17.37***	16.60**	3.225
	(4.277)	(6.882)	(3.949)
Severe	11.85***	1.931	-0.553
	(4.283)	(4.651)	(2.497)
Moderate	0.0364	1.622	-4.991**
	(3.018)	(3.634)	(2.359)
Constant	116.7***	185.9***	68.42***
	(6.997)	(7.341)	(3.624)
Observations	1,019	698	610
R-squared	0.721	0.631	0.520

Note: Control variables for state, district, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

For the districts of Colorado alfalfa markets, we show that the impact of drought increases with degree. Though the changes in price per ton are not the same magnitude of change as in the states analysis. For the Texas alfalfa markets, we see insignificant results for the first two indicators of drought but then a drastic change from extreme to exceptional conditions. Again, the grass market for Kansas displays inconsistent results, which may be due to aggregation.

As a robustness check for the DSCI at the districts, table 5.12 displays the weighted DSCI results for each statistically significant district. When aggregating the weather variable to the USDA AMS district we weighted DSCI by cow inventory and hay production to test the un-weighted DSCI. Analyzing the results, we find that the relationship and magnitude are very similar to the un-weighted analysis.

Table 5.12: Weighted District DSCI, 2000-2020

VARIABLES	(5) Colorado District Alfalfa Price	(6) Colorado District Alfalfa Price	(5) Texas District Alfalfa Price	(6) Texas District Alfalfa Price
CowDSCI	0.0577***		0.0639***	
	(0.0107)		(0.0168)	
HayProDSCI		0.0511***		0.0640***
		(0.0102)		(0.0158)
Constant	114.1***	114.3***	177.1***	177.8***
	(6.915)	(6.923)	(7.565)	(7.546)
Observations	1,019	1,019	698	698
R-squared	0.721	0.720	0.620	0.621

Note: Control variables for state, district, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

A key component behind the motivation of this research was to better understand how drought conditions affecting the entire state compared to when a district was alone experiencing drought. In table 5.13, we display a regression of drought at the district level and drought at the state level against district hay prices to see if there was a significant difference between the two reporting. From our findings we see that drought specifically in the district is statistically significant, while the state drought measure is not.

Table 5.13: State DSCI and District DSCI, 2000-2022

VARIABLES	(1) CO District Alfalfa Price	(1) TX District Alfalfa Price	(1) KS District Grass Price
DSCI - D	0.0601***	0.0539***	0.000874
	(0.0163)	(0.0189)	(0.0176)
DSCI - ST	-0.00686	0.0217	-0.00865
	(0.0289)	(0.0354)	(0.0207)
Constant	114.6***	174.6***	68.35***
	(6.839)	(8.317)	(3.638)
Observations	1,019	698	610
R-squared	0.720	0.619	0.512

Note: Control variables for district, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

All districts analyzed showed the same significance, that drought in the district is the most important. These results make sense as the district DSCI is a representation of the effects of drought on those local markets. It is also important to note that the coefficients with the district DSCI matched the previous model coefficient.

Our third hypothesis was, are districts more resilient to drought when the state is not experiencing drought? To test such, we created interactions between state and district drought levels. We averaged the drought categories across counties to match the scale outlined in the data section. In table 5.14, we see that in the instance of Colorado alfalfa markets, drought at the district level is more impactful than when the state is experiencing extreme drought. Upon testing the statistical difference between the two variables we cannot conclude that they are different. For Colorado and Texas, when the district is not in drought, state conditions do not influence hay prices (DNMES). Likewise, in Texas, extreme drought conditions at the district level only impact alfalfa prices when the state is also in extreme drought. These results suggest that regional hay markets are important for drought resilience and that there may be heterogeneity in market dynamics across regions. Kansas district grass markets have an inconclusive relationship with drought conditions, like previous regressions.

Table 5.14: Extreme Drought Comparison- District and State, 2000-2022

VARIABLES	(7) Colorado District Alfalfa Price	(7) Texas District Alfalfa Price	(7) Kansas District Grass Price
ESED	12.56***	11.88**	2.570
	(4.408)	(5.744)	(2.884)
DNMES	3.424	-1.491	-0.522
	(6.777)	(7.155)	(4.607)
SNMED	18.23***	2.694	1.282
	(4.808)	(4.920)	(2.984)
Observations	1,019	698	610
R-squared	0.720	0.614	0.512

Note: Control variables for state, district, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

The following tables (5.15-5.16) display our modeling upon the non-stationary district data. Given this data is non-stationary, to investigate the impacts using an OLS model we had to take the difference between current and previous year's drought and prices. We find that there is still a positive relationship between DSCI and hay prices, but no results are statistically significant.

Table 5.15: Non-Stationary DSCI, 2000-2022

VARIABLES	(4) Colorado District Grass ΔPrice	(4) Texas District Grass ΔPrice	(4) Kansas District Alfalfa ΔPrice
ΔDSCI	-0.00320	0.00427	0.00143
	(0.0432)	(0.0166)	(0.0117)
Constant	-10.61***	-11.28**	-0.478
	(3.490)	(5.036)	(3.852)
Observations	598	665	576
R-squared	0.194	0.071	0.040

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

Table 5.16: Non-Stationary Discrete DSCI

VARIABLES	(7) Colorado District Grass ΔPrice	(7) Texas District Grass ΔPrice	(7) Kansas District Alfalfa ΔPrice
ΔExceptional	-4.114	-13.99	8.197
	(15.60)	(12.27)	(5.008)
ΔExtreme	-0.946	2.583	6.646
	(12.91)	(4.495)	(5.149)
ΔSevere	0.824	1.170	-2.158
	(8.236)	(2.003)	(2.385)
ΔModerate	-1.293	-2.604	-3.527*
	(2.610)	(1.606)	(1.889)
Constant	-10.62***	-11.42**	-0.471
	(3.472)	(4.798)	(3.812)
Observations	598	665	576
R-squared	0.194	0.089	0.057

Note: Control variables for state, year, and month are not reported. Standard errors are two-way clustered by year and month. Standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1

Chapter 6 - Conclusion and Summary

This paper analyzes the impact of drought on state and district hay prices, using an ordinary least square model with fixed effects to account for unobserved fixed spatial and temporal factors that may influence hay markets. We applied these models to state hay prices recorded by the USDA NASS and district hay prices by USDA AMS. To estimate the magnitude of drought, we used the Palmer Drought Severity Index (PDSI) and the Drought Severity and Coverage Index (DSCI) estimated by the U.S drought monitor. From this drought data, we were able to create discrete variables representing typical drought severity categories, as well as interactions between local and widespread drought at the state and district level. The results of these models represent the net impact of drought on hay prices, reflecting both the direct impact of yield decline as well as market dynamics, such decreases in demand caused by forage and cattle inventory responses.

This research serves as the groundwork for future research in two major areas. First, once we understand the magnitude of the impact drought on hay prices, we can then seek to aid future research investigating the financial implications of culling cattle (or decreasing stocking rates) and the effects of on-farm-storage. Second, by estimating the local price response to drought, we can analyze the degree to which Federal forage insurance or safety net payments are sufficient to replace lost production.

This study has three primary results. First, most of our models, both state and district, reinforce the relationship between drought and hay prices as positive. When drought descends upon an area, hay price increases. Second, for each categorical increase in drought intensity, in our state analysis, there was a statistically significant increase in the magnitude of the effect of drought. As drought increases to extreme and exceptional levels, price impacts are larger. As for more granular impacts, some districts and hay types, such as Colorado alfalfa and Texas alfalfa, also displayed a similar trend. A portion of our data was non-stationary or reported multiple hay types, which may require further analysis of whether the data can be used for research purposes. Generally, we found that the aggregate drought status of neighboring states does influence state hay prices, but evidence of heterogeneity in the impact of regional markets in our analysis of state-district drought interactions for Colorado and Texas. These local and regional market dynamics are an important topic for further research.

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Appendix A -

Table A. 1: State Summary Statistics, PDSI

Variable	Obs	Mean	Std. dev.	Min	Max
Hay price	38,449	83.603	54.049	9.2	370
State PDSI	38,449	0.167	2.438	-9.09	10.75

Table A. 2: State Aggregate Hay Price, Missing Years

State	Years Missing	State Included
ALABAMA	1977-2015, 2020-2022	
ALASKA	1950-2015, 2020-2022	
ARIZONA	1950-1971	
ARKANSAS	1950-2071, 1971-2015, 2020-2022	
CALIFORNIA		Included
COLORADO		Included
CONNECTICUT	1950-2015, 2020-2022	
DELAWARE	1977-2015, 2020-2022	
FLORIDA	1950-2015, 2020-2022	
GEORGIA	1950-1955, 1982-2016, 2020-2022	
HAWAII	1950-2015, 2020-2022	
IDAHO		Included
ILLINOIS	1950 -1971	
INDIANA	1950-1971, 1997-2015, 2020-2022	
IOWA		Included
KANSAS		Included
KENTUCKY	1950-1971	Included
LOUISIANA	1977-2015. 2020-2022	
MAINE	1971-2015, 2020-2022	
MARYLAND	1977-2015, 2020-2022	
MASSACHUSETTS	1950-2015, 2020-2022	
MICHIGAN		Included
MINNESOTA		Included
MISSISSIPPI	1977-2015	
MISSOURI	1950-1971	Included
MONTANA	1950-1971	Included
NEBRASKA		Included
NEVADA		Included
NEW HAMPSHIRE	1971-2015, 2020-2022	
NEW JERSEY	1977-2015, 2020-2022	
NEW MEXICO		Included
NEW YORK		Included
NORTH CAROLINA	1977-2015, 2020-2022	
NORTH DAKOTA		Included
OHIO		Included
OKLAHOMA		Included

OREGON		Included
PENNSYLVANIA		Included
RHODE ISLAND	1971-2015, 2020-2022	
SOUTH CAROLINA	1950-2015, 2020-2022	
SOUTH DAKOTA		Included
TENNESSEE	1977-2015, 2020-2022	
TEXAS		Included
UTAH		Included
VERMONT	1971-2015, 2020-2022	
VIRGINIA	1977-2015, 2020-2022	
WASHINGTON		Included
WEST VIRGINIA	1977-2015, 2020-2022	
WISCONSIN		Included
WYOMING		Included

Table A. 3: State Summary Statistics, PDSI

Variable	Obs	Mean	Std. dev.	Min	Max
Hay price	38,449	83.603	54.049	9.2	370
State PDSI	38,449	0.167	2.438	-9.09	10.75

Table A. 4: State Summary Statistics, DSCI

Variable	Obs	Mean	Std. dev.	Min	Max
State DSCI	7,452	101.513	111.636	0	480.75

Table A. 5: Colorado Districts Summary Statistics

Districts	Variable	Obs	Mean	Std. dev.	Min	Max
Mountain West	Price	315	151.752	51.263	69.167	382.5
	DSCI	315	90.755	109.073	0	404.734
Northeastern	Price	431	170.482	72.969	55	400
	DSCI	431	107.197	111.279	0	406.179
Southeastern	Price	342	161.824	56.770	55	291.25
	DSCI	342	156.416	135.931	0	448.6
San Lois Valley	Price	296	154.297	50.823	62.083	275.625
	DSCI	296	143.188	136.665	0	495.25
Southwestern	Price	320	179.525	59.229	64.166	300
	DSCI	320	110.091	132.481	0	494.3273

Table A. 6: Texas Districts Summary Statistics

Districts	Variable	Obs	Mean	Std. dev.	Min	Max

North, Central and East	Price	456	125.105	59.704	21.951	300
	DSCI	456	117.773	114.63	0	486.887
Panhandle	Price	430	140.199	51.161	7.25	322.143
	DSCI	430	142.504	143.847	0	494.665
South	Price	242	88.695	31.351	9.167	159.25
	DSCI	242	134.952	132.526	0	480.798
West	Price	254	157.122	47.118	53.235	327.5
	DSCI	254	132.942	125.761	0	490.8

Table A. 7: Kansas District Summary Statistics

Districts	Variable	Obs	Mean	Std. dev.	Min	Max
North Central, Northeastern	Price	164	98.527	36.507	38.88	192.875
	DSCI	164	51.319	64.928	0	261.7232
Northwestern	Price	132	114.655	41.334	33.72	206.25
	DSCI	132	61.215	65.872	0	246.7
South Central	Price	328	120.157	55.428	41.47	250.423
	DSCI	328	120.387	133.768	0	446.737
Southeastern	Price	251	103.812	32.875	46.28	198.234
	DSCI	251	71.0112	98.795	0	463.938
Southwestern	Price	323	126.787	61.171	33.41	282.546
	DSCI	323	164.358	153.333	0	492.579

Table A. 8: Weighted Hay Price, Missing Years

Location	Years Missing	Districts Included
Antelope Valley - Mojave Desert, CA	2012-2020	
Arthur, IL	2012-2020	
Bethalto, IL	2012-2020	
Blythe - Parker, CA	2012-2020	
Central/East Central, NV	2012-2020	
Chino-Los Angeles, CA	2012-2020	
Crook, Deschutes, Jefferson, Wasco Co..		
Eastern Oregon, OR		
Escalon - Merced - Modesto - Turlock,..	2012-2020	
Hanford - Corcoran - Tulare, CA	2012-2020	
Hanford/Tulare/Visalia, CA	2012-2020	
Harney County, OR	2017-2020	
Idaho, ID	2012-2020	
Imperial Valley, CA	2012-2020	
Kern County, CA	2012-2020	
Klamath Basin, OR		
Lake County, OR		
Los Banos-Dos Palos, CA	2012-2020	
North Central/Northeast Kansas, KS	2010-2012	Included

Northern - Intermountain Areas, CA	2012-2020	
Northern, NV	2005-2006, 2012	
Northwest Kansas, KS	2011-2014	Included
Pacific Northwest, OR	2005-2014	
Petaluma, CA	2012-2020	
Region 1: North Inter-Mountain, CA	2005-2015	
Region 2: Sacramento Valley, CA	2005-2015	
Region 3: Northern San Joaquin Valley..	2005-2015	
Region 4: Central San Joaquin Valley,..	2005-2015	
Region 5: Southern California, CA	2005-2015	
Region 6: Southeast California, CA	2005-2015	
Sacramento Valley, CA	2012-2020	
Shelbyville, IL	2005-2006,2012	
South Central Kansas, KS		Included
South-Central Coastal Areas, CA	2012-2020	
Southeast Hay, AL		
Southeast Kansas, KS		Included
Southwest Kansas, KS		Included
Tracy-Patterson-Stockton, CA	2012-2020	
Washington-Oregon (Columbia Basin) Ha..		
Western Fresno-Madera Counties, CA	2012-2020	
Western, NV	2012-2020	

Table A. 9: Simple Hay Prices, Missing Years

Location	Years Missing	Districts Included
Central Illinois, IL	2014-2020	
Central and Western, OK	2010-2020	
Central, OK	2010-2020	
Crook, Deschutes, Jefferson, Wasco Co..	2006-2020	
East River-So. Dakota, SD	2000-2007,2013-2020	
Eastern Oregon, OR	2006-2020	
Eastern, OK	2010-2020	
Harney County, OR	2006-2020	
Harrisonburg, VA		
High Plains Hay Exchange, WY	2000-2022	
Iowa, IA	2000-2001,2018-2020	
Kansas, KS	2014-2020	
Klamath Basin, OR	2000-2001,2006-2020	
Lake County, OR	2006-2020	
Montana Hay, MT		
Montana, MT	2014-2020	

Mountain Area, CO		Included
Nebraska, NE	2000-2001	
North, Central and East Texas, TX		Included
Northeast Colorado, CO		Included
Northern Illinois, IL	2014-2020	
Panhandle Feedlot Area, OK	2009-2020	
Panhandle, TX		Included
Salt Lake City, UT	2000-2003,2006-2020	
San Luis Valley, CO		Included
South Texas, TX		Included
South Western Colorado, CO		Included
South-Central Coastal Areas, CA	2006-2020	
Southeast Colorado, CO		Included
Southwest Minnesota, MN	2000-2001, 2005-2020	
Southwestern South Dakota, SD		
W.S. West, IL	2014-2020	
West Texas, TX		Included
Western Nebraska, NE		
Western Slope Area, CO		Included
Wisconsin, WI	2003-2020	
Wyoming Video Hay Auction, WY	2000-2004	
Wyoming, WY		

Figure A. 1: State Hay Price, Stationary

```
Fisher-type unit-root test for price
Based on augmented Dickey-Fuller tests
--------------------------------------
H0: All panels contain unit roots           Number of panels       =    876
Ha: At least one panel is stationary        Avg. number of periods =  25.19

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(1752) P      7133.9578       0.0000
 Inverse normal            Z       -57.4585       0.0000
 Inverse logit t(4384)     L*      -64.6373       0.0000
 Modified inv. chi-squared Pm       90.9198       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Figure A. 2: State PDSI, Stationary

```
Fisher-type unit-root test for PDSI
Based on augmented Dickey-Fuller tests
--------------------------------------
H0: All panels contain unit roots           Number of panels       =    888
Ha: At least one panel is stationary        Avg. number of periods =  47.68

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Not included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(1752) P      1.93e+04       0.0000
 Inverse normal            Z     -120.6602       0.0000
 Inverse logit t(4384)     L*    -180.0878       0.0000
 Modified inv. chi-squared Pm     297.0266       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Figure A. 3: State DSCI, Stationary

```
Fisher-type unit-root test for dsci
Based on augmented Dickey-Fuller tests
--------------------------------------
H0: All panels contain unit roots           Number of panels  =     27
Ha: At least one panel is stationary        Number of periods =    276

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(54)    P      527.5520       0.0000
 Inverse normal             Z      -18.5204       0.0000
 Inverse logit t(139)       L*     -28.0378       0.0000
 Modified inv. chi-squared Pm       45.5676       0.0000
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Figure A. 4: Colorado Hay Price, Non-Stationary

```
Fisher-type unit-root test for price
Based on augmented Dickey-Fuller tests
--------------------------------------
H0: All panels contain unit roots            Number of panels       =      5
Ha: At least one panel is stationary         Avg. number of periods = 134.00

AR parameter: Panel-specific                 Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                   ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        15.9482       0.1011
 Inverse normal            Z        -0.7018       0.2414
 Inverse logit t(29)       L*       -0.5966       0.2777
 Modified inv. chi-squared Pm        1.3300       0.0918
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Figure A. 5: Texas Non-Alfalfa Price, Non-Stationary

```
Fisher-type unit-root test for Dprice
Based on augmented Dickey-Fuller tests
--------------------------------------
H0: All panels contain unit roots           Number of panels       =      4
Ha: At least one panel is stationary        Avg. number of periods = 170.00

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(8)      P       6.7400       0.5649
 Inverse normal              Z       0.6022       0.7265
 Inverse logit t(24)         L*      0.7085       0.7573
 Modified inv. chi-squared Pm      -0.3150       0.6236
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Figure A. 6: Kansas Alfalfa Price, Non-Stationary

```
Fisher-type unit-root test for Dprice
Based on augmented Dickey-Fuller tests
--------------------------------------
H0: All panels contain unit roots          Number of panels       =      5
Ha: At least one panel is stationary       Avg. number of periods = 117.60

AR parameter: Panel-specific               Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                 ADF regressions: 1 lag
------------------------------------------------------------------------------
                                  Statistic      p-value
------------------------------------------------------------------------------
 Inverse chi-squared(10)   P        14.7093       0.1430
 Inverse normal            Z        -1.1963       0.1158
 Inverse logit t(29)       L*       -1.2395       0.1125
 Modified inv. chi-squared Pm        1.0530       0.1462
------------------------------------------------------------------------------
 P statistic requires number of panels to be finite.
 Other statistics are suitable for finite or infinite number of panels.
------------------------------------------------------------------------------
```

Table A. 10: Ratio of Milk Cows to Beef Cows, 1950-2022

state	Percentage of Milk Cows to Beef Cows
Arizona	0.666
California	1.570
Colorado	0.145
Idaho	0.639
Illinois	0.289
Iowa	0.448
Kansas	0.148
Kentucky	0.131
nMichigan	3.176
Minnesota	2.296
Missouri	0.078
Montana	0.013
Nebraska	0.103
Nevada	0.080
New Mexico	0.290
New York	17.248
North Dakota	0.202
Ohio	1.725
Oklahoma	0.106
Oregon	0.228
Pennsylvania	6.232
South Dakota	0.122
Texas	0.102
Utah	0.290
Washington	0.844
Wisconsin	13.353
Wyoming	0.027

.

Table A. 11: Ratio of Irrigated Hay, 1950- 2022

State	Alfalfa Hay Irrigation		Non-Alfalfa Hay Irrigation
Arizona	0.999	Arizona	0.949
California	0.965	California	0.724
Colorado	0.854	Colorado	0.654
Idaho	0.808	Idaho	0.506
Illinois	0.003	Illinois	0.002
Iowa	0.001	Iowa	0.002
Kansas	0.250	Kansas	0.021
Kentucky	0.002	Kentucky	.
Michigan	0.012	Michigan	0.009
Minnesota	0.017	Minnesota	0.005
Missouri	0.007	Missouri	0.002
Montana	0.413	Montana	0.390
Nebraska	0.327	Nebraska	0.087
Nevada	0.996	Nevada	1
New Mexico	0.952	New Mexico	0.645
New York	0.002	New York	0.004
North Dakota	0.013	North Dakota	0.006
Ohio	0.001	Ohio	0.002
Oklahoma	0.104	Oklahoma	0.021
Oregon	0.875	Oregon	0.545
Pennsylvania	0.002	Pennsylvania	0.003
South Dakota	0.042	South Dakota	0.014
Texas	0.525	Texas	0.073
Utah	0.909	Utah	0.886
Washington	0.707	Washington	0.418
Wisconsin	0.006	Wisconsin	0.017
Wyoming	0.731	Wyoming	0.824