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Climate & Consolidation in the U.S. Beef Cow Sector

Nathan D. DeLay, Daniel F. Mooney, John P. Ritten

The ability of livestock producers to adapt to climate change may vary by operation scale, with implications for consolidation in the beef cattle industry. This paper examines changes in the U.S. beef cow sector across different herd size classes in response to climate extremes. We show that persistent exposure to drought and extreme heat shift beef cow inventories from larger to smaller herds, leading to a contraction in the beef cow herd. However, these conditions lead to a net increase in the number of beef cow operations. The overall effect is fewer animals distributed across more small-scale farms.

Key words: beef cattle, industry consolidation, climate change

Introduction

The beef cattle sector is vitally important to U.S. agriculture, contributing 17% of all agricultural commodity sales nationwide at over $88 billion and supporting over 721,000 jobs (English et al., 2020; USDA ERS, 2023a). Domestic producers supply a competitive U.S. beef export industry, worth over $8 billion annually (USDA FSA, 2024). Climate risks represent a serious threat to cattle production. Drought causes forage loss, inhibits animal weight gain, and raises production costs, all leading to lower incomes for ranching families and their rural economies (Nardone et al., 2010; Patalee and Tonsor, 2021a; Briske et al., 2021; Cheng, McCarl, and Fei, 2022; Fleming-Munoz, Whitten, and Bonnett, 2023). On-farm impacts of drought can lead to greater food insecurity for downstream consumers (Rojas-Downing et al., 2017; Godde et al., 2021). Because risk management programs for livestock are less popular than those for crop production, beef cattle producers may be more vulnerable to climate shocks (Rodziewicz, Dice, and Cowley, 2023; Hrozencik, Perez-Quesada, and Bocinsky, 2024).

Estimates of future climate change predict drought will become both more common and more intense, particularly in the traditional cattle-dependent Western and Great Plains regions of the United States (Briske et al., 2021; IPCC, 2022). The role of operation scale—which we measure using size of the cow herd—in managing drought and other climate risks is uncertain. Future warming trends may have disparate impacts on cattle producers based on the risk mitigation options available to them (Hrozencik, Perez-Quesada, and Bocinsky, 2024). Large well-capitalized operations who own or lease greater amounts of pasture or have access to public grazing alternatives may reduce their stocking rates less dramatically than ranchers with limited substitutes (Briske et al., 2021; Godde et al., 2021). Conversely, small operations are more diversified with greater dependence on off-farm income sources, which may allow them to maintain relatively stable herds despite adverse weather or general market conditions (Bastian et al., 2006). Inventory reductions may differ across production scales in response to climate change. The combined effects could lead

Nathan D. DeLay (corresponding author, nathan.delay@colostate.edu) is an assistant professor, Daniel F. Mooney is an associate professor, and John P. Ritten is a professor in the Department of Agricultural and Resource Economics at Colorado State University.
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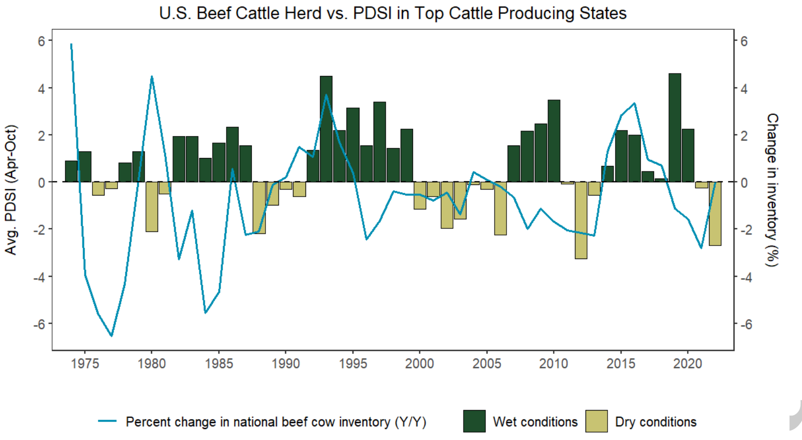

Figure 1. Palmer Drought Severity Index (PDSI) and Change in National Beef Cow Inventory, 1975-2022

to greater concentration of beef production in certain regions or at certain scales. Understanding these dynamics is key to predicting long-run impacts of climate change on U.S. animal agriculture.

As of Jan. 1, 2024, the U.S. had the smallest beef cow herd since 1951, in part due to persistent and severe droughts in the Western and Great Plains regions (NOAA NCEI, 2022; USDA ERS, 2023b). While other factors are also at play in determining the cattle cycle—such as cattle prices, feed costs, inflation, and supply chain disruptions—the biological nature of cattle production means that even short-term drought could lead to significant long-term disruptions in beef production. Figure 1 shows changes in the national beef cow herd alongside the Palmer Drought Severity Index (PDSI) for the largest beef cattle producing states in the U.S. extending back to 1974.[1] Dry periods (PDSI values below zero) sometimes coincide with periods of beef cow herd declines as producers respond to deteriorating forage quantity and quality. Evaluating the effect of drought on the beef herd while controlling for other factors like prices, costs, and time-invariant local conditions could provide further evidence of this relationship.

The purpose of this paper is to estimate the impact of drought on consolidation within the cow-calf sector of the U.S. beef industry.[2] We use county-level data from the U.S. Department of Agriculture (USDA) Census of Agriculture from 1974 to 2022 to observe changes in the number of beef cattle operations and beef cattle inventories across different herd size classes in response to local climate conditions. Results confirm that persistent drought leads to smaller average herd sizes, but an unexpected rise in the total number of beef cow operations. Liquidation within a single large operation may allow multiple small farms to expand into cattle production. During wet periods, the pattern is reversed—leading to slightly fewer farms with larger average herd sizes. Previous studies have yet to consider the dual impacts of climate change on both herd size and net farm entry/exit within the cattle industry. Our findings suggest that future warming in cattle-dependent regions could cause an inward shift in cattle production that decreases rather than increases concentration in the cow-calf sector.

We extend the existing body of work on climate change and agriculture by looking at the effects of drought on the number of beef cattle farms and inventories, but also their distributions

[1] The PDSI was calculated for the grazing season of April through October for states with at least 1 million head of beef cows including Texas, Oklahoma, Missouri, Nebraska, South Dakota, Kansas, and Montana based on data from the 2022 U.S. Census of Agriculture.

[2] In this study, we use the term consolidation as it best describes the structural changes we observe in the cow-calf sector across different herd size classes. We define consolidation in this context as a shift in the distribution of farms and beef cows from small to large operations. Though we do not examine the potential link between consolidation and market power, we leave this question for future consideration.

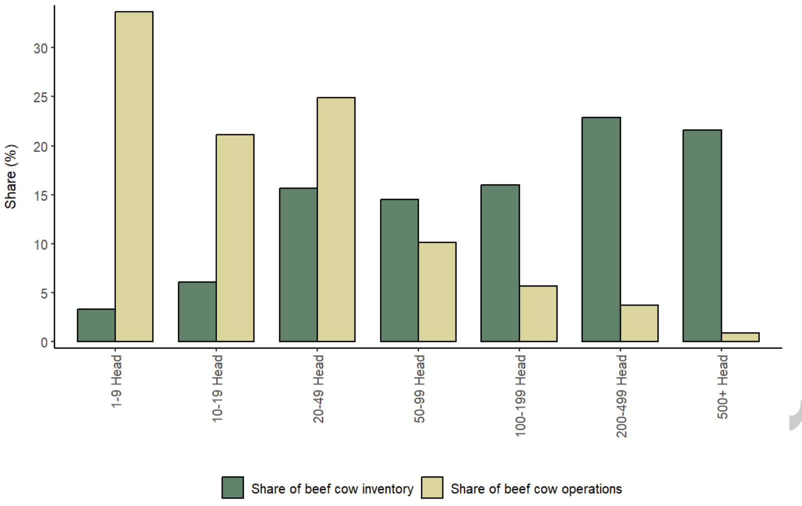

Figure 2. Beef Cattle Operations and Inventory by Herd Size, 2022

across different scales of production. Our result shed light on the role of climate in cattle industry consolidation, revealing previously unknown climate adaptation mechanisms at work within the U.S. animal agriculture sector. In the next section, we set the stage for our analysis by providing a brief background on the cow-calf sector and the relevant literature. We then describe our study variables, dataset, and empirical strategy and present the results. We conclude with a discussion of possible mechanisms and policy implications.

Background

Over 620,000 U.S. farms had a beef cow herd as of 2022, down from 729,000 in 2017 (USDA NASS, 2017, 2022). Unlike the dairy or pork sectors, which benefit disproportionately from economies of scale due to confined feeding systems, cow-calf production has not experienced consolidation on a large scale (MacDonald, Hoppe, and Newton, 2018). The average beef cow herd size in 2022 (the most recent USDA data available) was 47 compared to 42 in 2002. While more dispersed than other animal agriculture industries, Figure 2 shows that beef cattle production remains skewed toward larger operations. Farms with at least 100 head of beef cows made up just over 10% of cattle operations in 2022, but were responsible for nearly 61% of the national beef cow herd that year.

Figure 3 shows how the distribution of U.S. beef cattle operations has changed over the last 40 years. While the number of farms with fewer than 50 head of beef cattle has fallen steadily over time, the number of large operations has not grown significantly. Figure 4 shows that the share of inventory managed by the smallest herds (those with fewer than 20 head) has been relatively stable since the 1970s. Inventory in medium sized herds (those between 20 and 99 head) have declined more noticeably, shifting to herds with 200 or more beef cows, which have seen modest growth. However, the cow-calf sector has generally not experienced the kind of consolidation seen in the cattle feeding and meat processing sectors of the beef system (MacDonald, Hoppe, and Newton, 2018; MacDonald, Dong, and Fuglie, 2023; Saitone et al., 2023). Because of this, concentration in the upstream portion of the beef supply chain has received less attention.

The cattle cycle is shaped in large part by weather trends due to the importance of forage in beef production (Rojas-Downing et al., 2017). Livestock producers adjust their herd size each year to maximize their strategic goals, conditional on their expectations about forage availability, general market conditions, and other farm and farmer characteristics (Ritten et al., 2010). Moreover, some operators or landowners may also choose to exit or enter livestock production in a given year

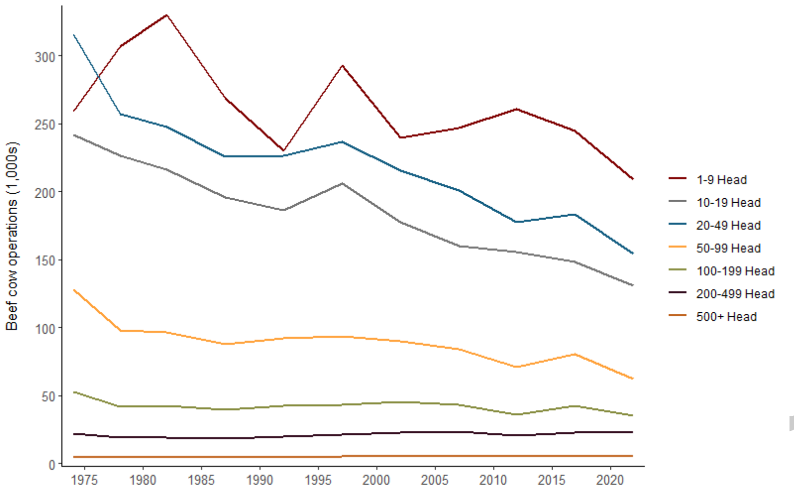

Figure 3. Beef Cattle Operations by Herd Size, 1974-2022

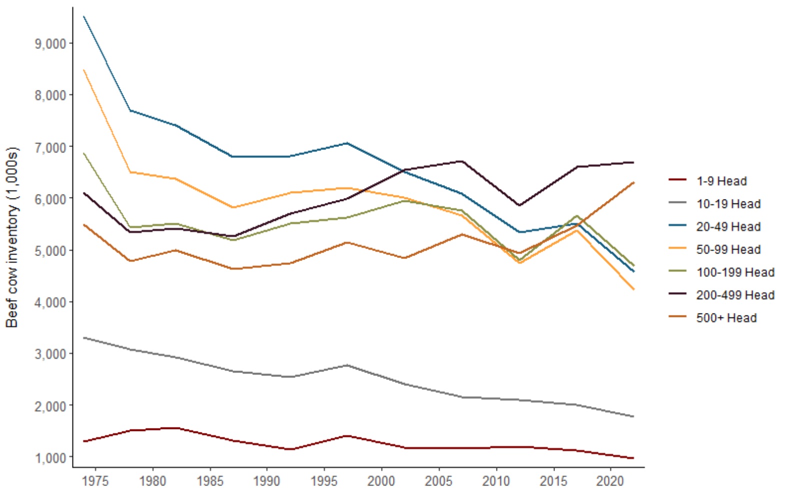

Figure 4. Beef Cow Inventory by Herd Size, 1974-2022

depending on these factors, and on their preferences and market signals for owning livestock versus producing hay or renting out their land (Bastian et al., 2006). Initially, drought increases forage and crop prices, causing livestock producers to cull their breeding stock and retain or purchase fewer replacement heifers, which reduces cattle prices in the near-term as the supply of beef cattle coming to market rises (Aadland and Bailey, 2001). Eventually, beef cattle prices rise above their initial level as the effects of herd liquidation set in (Leister, Paarlberg, and Lee, 2015).

Inventory dynamics are particularly important in beef cattle production due to the biological nature of the cattle cycle. Patalee and Tonsor (2021b) show the importance of temperature during different seasons of the cow-calf production year on inventories. They also consider spatial lag effects of inventory changes in neighboring states on local herd sizes, finding evidence for climate adaptation through spatial reallocation. Belasco, Cheng, and Schroeder (2015) motivate the development of an weather index insurance product for finished cattle by identifying the effects of extreme heat and cold on cattle feeder profits.

In the broader context, the literature on climate change in agriculture is well established. Seminal work by Schlenker and Roberts (2009) identifies heat damage thresholds for corn and soybeans, while Chambers and Pieralli (2020) find that adverse weather has stifled agricultural productivity growth in the U.S. However, the long-run effects of climate change on agriculture are not well known due to uncertainty around the role of adaptation (Burke and Emerick, 2016). Climate adaptation often appears as the capitalization of future climate change into land values—the so called Ricardian method (Mendelsohn, Nordhaus, and Shaw, 1994). Research has shown the potential for agricultural technology to mitigate the effects of climate (Kurukulasuriya, Kala, and Mendelsohn, 2011; Porsche, Gandorfer, and Bitsch, 2018). Others emphasize adaptation to warming through shifts in agricultural land use (Seo and Mendelsohn, 2008; Cho and McCarl, 2017). Focusing on U.S. animal agriculture, Wang and McCarl (2021) predict a significant shift in land use toward beef cattle grazing at the expense of other livestock. The use of livestock insurance and disaster programs related to climate change will also play an increasingly important role (Hrozencik, Perez-Quesada, and Bocinsky, 2024).

Relatively few studies have considered the role of climate in industry consolidation. In their study of U.S. manufacturers, Ponticelli, Xu, and Zeume (2023) find that small firms are more susceptible to temperature shocks, and the resulting energy cost increases, than large firms. Prolonged exposure to extreme temperatures is associated with greater concentration of manufacturing among large plants. In the agricultural sector, Lacy, Orazem, and Schneekloth (2023) show that regions with less favorable climates tend to have larger crop farms, possibly the result of scale economies required to adopt climate-adaptive technologies. Rodziewicz, Dice, and Cowley (2023) find that sustained drought can significantly reduce average beef cattle herd sizes, suggesting a connection between weather and concentration in cattle production. However, to the authors' knowledge, no study has directly explored the distributional impacts of climate across scales of production in the cow-calf sector of the beef industry. In the following section, we explain the data used to investigate this issue.

Data

The primary source for livestock data in our analysis are the Censuses of Agriculture administered by the USDA National Agricultural Statistical Service (NASS) every 4-5 years. They report the total number of beef cow operations (cow-calf producers) and the total number of beef cows (inventory) in each county as of Dec. 31st of the Census year. Since the 1970s, the USDA has dis-aggregated these numbers into 7 herd size classes (1-9 head, 10-19 head, 20-49 head, 50-99 head, 100-199 head, 200-499 head, 500 head or more), allowing us to observe changes in the distribution of cattle and operations across groups over time.

We collect this data for all U.S. counties with reported values for Census years 1974, 1978, 1982, 1987, 1992, 1997, 2002, 2007, 2012, 2017, and 2022, giving us up to 11 observations per county.[3] Starting in the early 2000's, USDA NASS began suppressing data on cattle operations and inventories in the interest of protecting farmer privacy. In years when the number of operations within a given herd size is small, NASS may suppress the beef cattle inventory reported for that year to prevent identifying the herd size of an individual operation. This results in a higher proportion of missing values in the later years of our dataset, particularly for cattle inventory numbers in the largest herd size classes.

To maintain the most complete data and to focus on cattle-dependent counties, we limit our analysis to counties that have an average of 10,000 head of beef cattle or more over the observation period. Together these counties were responsible for over 56% of the entire U.S. beef cow herd in 2022. Given our interest in within-county changes across herd scale categories, we also restrict our

[3] The data for 2002 and after are available through the USDA QuickStats database (https://quickstats.nass.usda.gov/). Archived data prior to 2002 was obtained from the University of Michigan Inter-university Consortium for Political and Social Research (ICPSR) (https://www.icpsr.umich.edu/web/pages/index.html).

analysis to county-years with complete data (non-missing) for each size group. This allows us to fully observe animals and farms shifting in and out of size classes over time.[4] After applying our sample-selection criteria, our estimation dataset contains 1,171 counties with complete data on beef cow operations and 854 counties with complete data on beef cow inventories, mostly in Western and Great Plains states. Maps identifying the sample counties are shown in Figures A1 and A2 of the supplemental appendix.

We collect several climate measures to examine the relationship between beef cattle industry consolidation and drought. First, we obtain the PDSI from the U.S. Government's National Oceanic and Atmospheric Administration (NOAA).[5] The PDSI is a soil moisture index that takes into account both temperature and precipitation. Values range from -10 to +10 with -4 indicating extreme drought, +4 indicating extreme precipitation, and zero corresponding to normal conditions. Importantly, the PDSI is standardized by location, meaning values are interpreted relative to the long-run expectations for a region. The finest available unit of observation for historical PDSI data is the climate division level. Climate divisions encompass multiple counties—on average about 9 counties belong to each climate division though numbers vary by state.[6]

Monthly PDSI values are averaged across the standard beef cattle grazing season of April through October for each year from 1970 to 2022. Due to the cyclical nature of beef cattle production, it is appropriate to use recent climate history to explain cattle and farm operation numbers, which we only observe in Census years. We create a moving average of the grazing-season PDSI for the periods between each Census. For 1978 and 1982, this is a 4-year moving average ending in the observed Census year and a 5-year moving average for all other periods.[7]

In addition to the PDSI, we collect weather data more commonly seen in research on the effects of climate change on agricultural production (Mendelsohn, Nordhaus, and Shaw, 1994; Schlenker, Hanemann, and Fisher, 2006; Deschenes and Greenstone, 2007; Seo and Mendelsohn, 2008; Schlenker and Roberts, 2009; Burke and Emerick, 2016). We collect daily precipitation and temperature data from the the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) housed at Oregon State University.[8] We observe the total amount of rainfall received by each county throughout the grazing season (April to October).

Because crops and forage respond non-linearly to heat exposure, we also collect cumulative degree-days (heat units) above 34°C (DD34C) between April and October, a standard threshold at which crop damaging effects set in (Schlenker, Hanemann, and Fisher, 2006). Degree-days are calculated by fitting a sine function to daily temperature minimum and maximum values following Schlenker and Roberts (2009).[9] As with the PDSI, we construct recent-period moving averages for precipitation and DD34C. Precipitation and DD34C data are available at the county level for 1980 and after.

Changes in cattle operations and herd size are also influenced by cattle prices and production costs. We control for output prices using national calf prices received by cattle producers reported by USDA NASS monthly, from which we compute annual averages. Drought conditions deplete local forage availability, requiring operators to buy supplemental feed, making feed prices the most weather-sensitive operating cost faced by cattle producers. To control for contemporaneous increases in production costs that may also affect herd size and the number of livestock operations, we collect

[4] We did not employ the long-difference approach àla Burke and Emerick (2016) due to the discontinuous observation periods of the Census of Agriculture. As they point out, differencing two individual years would add noise to the analysis. We opt for a modified panel structure which takes into account recent history.

[5] PDSI data were obtained from the National Climate Data Center (NCDC) online database https://www1.ncdc.noaa.gov/pub/data/.

[6] Weighted averages of weather data from meteorological stations within each climate division were used to construct the PDSI each month. In total there are 344 climate divisions in the continental U.S. A description and map can be found here: https://www.ncei.noaa.gov/access/monitoring/dyk/us-climate-divisions.

[7] Our results are robust to alternative calculations of the PDSI moving average.

[8] These data are available at the UC Davis Ag Data News site: https://asmith.ucdavis.edu/data/prism-weather.

[9] A description of the degree-day formula can be found here: https://asmith.ucdavis.edu/data/prism-weather.

state-average hay prices in dollars per ton for each of the observed years in our analysis. Unlike feeder cattle prices, which are generally determined in a national market, cattle forage markets tend to be localized with prices varying within states.[10] We capture changes in relative profitability across regions and over time by including the ratio of cattle prices to hay prices as a variable in our models.

Summary statistics for the pooled dataset are presented in Table 1. The average county in our sample has 416 cow-calf operations raising nearly 29,000 head of beef cattle. The average herd size in our sample is over twice the national average at 96.5 head per operation. Because of our focus on cattle-dependent regions, our sample is geographically skewed—68% of our observations belong to the West, Northern Plains, and Southern Plains regions. This is reflected in the distribution of farms and inventories across herd size classes. For the typical county in our sample, farms with fewer than 10 beef cows make up about 22% of the total number of operations, but manage less than 2% of the beef cow herd. Conversely, the average county has 5.5 operations with 500 head of beef cows or more—about 2.5% of all farms—but these operations are responsible for 24% of the county's beef cow herd.

The moving average of the grazing-season PDSI appears normally distributed around a mean of 0.34—indicating close to normal conditions. The average county can expect about 53 cm of rainfall and 11.4 degree-days above 34°C during the grazing season based on the recent-period mean. DD43C are notably higher in the drought-impacted years of 2002 and 2012. The ratio of calf (measured in \$s per cwt) to hay prices (\$s per ton) average about 1.2 over the observation period, ranging from a low of 0.8 in 1974 to a high of 1.4 in 2017.

Empirical Model

We estimate the impact of local climate on the number of beef cow operations and inventory separately for each herd size group. To accommodate errors that may be correlated across production scales, we jointly estimate the following system of equation using the more efficient seemingly unrelated regression (SUR) approach from Zellner (1962):

$$\boldsymbol{y}_{it} = \boldsymbol{\alpha}_i + \boldsymbol{\tau}_t + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{it}. \tag{1}$$

The vector $\boldsymbol{y}_{it}$ represents the dependent variables of beef cattle operations and beef cattle inventories belonging to each herd size category in county i during year t. We take the natural logarithm of both dependent variables in order to compare proportional changes across herd size groups.[11] $\boldsymbol{\alpha}_i$ is a vector of county fixed-effects that control for time-invariant characteristics that may affect the outcomes in each equation such as pastureland availability, proximity to auction markets, and long-run climate expectations. To capture temporal factors that affect all producers in the same time period, we include a vector $\boldsymbol{\tau}_t$ of year fixed-effects. $\boldsymbol{x}_{it}$ is a matrix of explanatory variables including the moving averages of local weather variables and the natural log of the cattle-to-hay price ratio as of year t.

The above system of equations is estimated separately for operations and inventories, each of which includes 8 equations; one for the total number of animals and farms, and one for each of the 7 size classes (1-9 head, 10-19 head, 20-49 head, 50-99 head, 100-199 head, 200-499 head, 500 head or more). Additionally, for each dependent variable we estimate the SUR using 2 sets of climate variables for comparison: one with the moving average of the PDSI and one with the moving averages of DD34C and precipitation, respectively. Initially, we specify a linear relationship between the PDSI and beef cattle production. In the latter case, we model non-linear weather effects

[10] Ideally, we would observe feed prices at the county level. However, this data is not readily available so we are left with state-level observations as second-best.

[11] For example, the loss of a single farm in the 500 plus herd size category may represent a significant reduction in the number of farms in that group, but the same loss among farms with 1-9 head—a group which contains a much larger share of beef cattle operations—may represent a relatively small change. Log transformations allow us to compare these proportional changes.

Table 1. Summary Statistics

VARIABLES	N	Mean	Std. Dev.	Min.	Max.
Beef cow operations: total	9,659	416.26	317.04	19.00	2,458.00
Beef cow operations: 1-9 head	9,659	105.50	122.91	1.00	1,297.00
Beef cow operations: 10-19 head	9,659	83.53	85.02	1.00	685.00
Beef cow operations: 20-49 head	9,659	114.84	97.08	1.00	721.00
Beef cow operations: 50-99 head	9,659	56.20	39.13	1.00	346.00
Beef cow operations: 100-199 head	9,659	31.91	21.85	1.00	284.00
Beef cow operations: 200-499 head	9,659	18.78	16.29	1.00	193.00
Beef cow operations: 500+ head	9,659	5.51	6.71	1.00	109.00
Beef cow inventory: total[a]	4,704	28,683.12	16,002.35	5,953.00	184,688.00
Beef cow inventory: 1-9 head	4,704	497.55	596.80	2.00	5,251.00
Beef cow inventory: 10-19 head	4,704	1,049.20	1,180.79	19.00	9,319.00
Beef cow inventory: 20-49 head	4,704	3,256.80	3,010.48	82.00	21,651.00
Beef cow inventory: 50-99 head	4,704	3,847.30	2,805.49	117.00	24,167.00
Beef cow inventory: 100-199 head	4,704	4,972.27	3,348.88	354.00	37,774.00
Beef cow inventory: 200-499 head	4,704	7,207.67	5,509.01	623.00	56,114.00
Beef cow inventory: 500+ head	4,704	7,852.34	9,031.91	1,200.00	127,214.00
Avg. herd size	4,704	96.49	64.05	14.19	590.91
PDSI (5-year moving avg.)	9,659	0.34	1.44	-5.70	6.00
Degree-days above 34°C (5-year moving avg.)[b]	7,188	11.39	16.53	0.00	197.50
Precipitation (cm, 5-year moving avg.)[b]	7,188	53.34	24.16	3.41	135.23
Cattle hay price ratio[c]	9,659	1.19	0.34	0.58	2.47
Pacific	9,659	0.06	0.25	0.00	1.00
West	9,659	0.21	0.41	0.00	1.00
Northern Plains	9,659	0.21	0.41	0.00	1.00
Southern Plains	9,659	0.26	0.44	0.00	1.00
Lake States	9,659	0.00	0.07	0.00	1.00
Corn Belt	9,659	0.08	0.27	0.00	1.00
Delta	9,659	0.06	0.23	0.00	1.00
Appalachia	9,659	0.04	0.21	0.00	1.00
Southeast	9,659	0.06	0.24	0.00	1.00

Notes: The sample is restricted to counties with an average of at least 10,000 head of beef cows across the years observed. To be included in the estimation sample, values for each herd size class must be non-missing and non-zero. [a] Due to suppression of cattle inventory numbers in certain years, the number of observations for inventories are lower than those for operations. [b] Data for degree-days and precipitation are for the period 1987 and after due to data limitations. [c] Ratio of national average calf prices received by producers ($s per cwt) relative to state-level hay prices ($s per ton).

using a quadratic specification for precipitation and the square root of DD34C following Schlenker, Hanemann, and Fisher (2006).[12]

We use the “sureg” command in Stata 18 to estimate the above system of equations. However, this approach does not provide a flexible way to accommodate the large number of county fixed-effects in our dataset. To overcome this, we manually mean-difference all of the variables for each observation to eliminate the fixed-effect α_i, then run the SUR as pooled cross-sectional data. A BreuschâĂŞPagan test rejects the independence of equation errors at the 0.01 level in all cases, supporting the use of SUR. In addition to being correlated across equations, disturbances may also be correlated across counties within the same state. We correct for this possibility by clustering our standard errors at the state level.

[12] Schlenker, Hanemann, and Fisher (2006) find that the square root function provides a good approximation of the diminishing marginal impact of heating degree-days on farmland values. We find the square root function performs similarly well for cattle production outcomes relative to other functional forms.

Before explaining our results, we note several empirical limitations of our dataset and empirical approach. First, the large number of missing values for beef cow inventories restricts the sample available to run the SUR models. Missing inventory values are primarily the result of data suppression efforts by the USDA NASS designed to protect sensitive producer information, while the count of farm operations is not subjected to disclosure review.[13] Second, as a result of the log-transforming the dependent variables, we drop zero values for beef cow inventories and operations in our main SUR estimation. Recent literature has pointed out the outsize influence that zero-value transformation decisions can have on estimated marginal effects (Bellemare and Wichman, 2020; De Brauw and Herskowitz, 2020; Aihounton and Henningsen, 2021; Mullahy and Norton, 2023). In response, we take a conservative approach, dropping zero-value observations from our estimation sample. Out of 13,363 county-year observations that satisfy our minimum beef cow herd threshold, 4,704 have complete and non-zero data for beef cow inventories while 9,659 have complete and non-zero data for beef cow farms across all herd size classes.

We acknowledge the severe effect this approach has on our sample size. To test for the sensitivity or our results to these sample-selection decisions, we subject our main estimation strategy to a battery of robustness checks and alternative empirical strategies. Our main findings presented in the following section are broadly robust to these empirical choices. Additional details and robustness check results are described in Section .

Results

We report our main SUR results for beef cow operations in Tables 2 and 3 and those for beef cow inventories in Tables 4 and 5. In general, we find that persistent drought and exposure to extreme heat shift the distribution of beef cow farms and inventories from larger to smaller. The outcome is an expected net contraction in the total beef cow herd, but an unexpected increase in the overall number of beef cow operations. We discuss each set of results in turn. A graphical summary of the estimated marginal effects of our main climate variables across all equations is shown in Figure 5. Starting in Table 2, we see that a one unit increase in the 5-year average PDSI is associated with a reduction in the total number of cow-calf operations by about 2.2% overall.[14] The estimated impact is statistically significant at the 0.01 level. These changes are additional to the existing cattle cycle, meaning drought can exacerbate declines in the overall cattle herd during a contraction phase. However, the relationship varies significantly across herd scales.

For small-scale operations (those with fewer than 50 head of beef cows) the relationship between the 5-year moving average PDSI and the number of cattle farms is negative. A one-unit increase in the PDSI is associated with a 5.4% reduction in the number beef farms in the 1-9 head category, a 4.1% reduction in farms with 10-19 head, and a 2.7% reduction in farms with 20-49 head; which is consistent with the expectation that livestock producers increase their herd size when weather conditions are favorable to improved forage availability. The relationship is reversed for large-scale operations (those with at least 100 beef cows). The same one-unit increase in the average PDSI generates an expected 3.9%, 7.8%, and 5.7% increase in farms with at least 100, 200, and 500 head of beef cows, respectively.

It is notable that farms in the 200-499 head class appear to be the most responsive to drought, despite the fact that this class both loses farms to the 500 plus group and gains farms from size categories below it. A test for equality of coefficients across equations confirms that the 200-400 head farm size has the largest association with the PDSI. For operations with between 50 and 99 head, the coefficient is near zero and statistically insignificant, implying that a roughly equal number

[13] From the 2017 USDA Census of Agriculture, Volume 1, Chapter 1, Appendix A. Census of Agriculture Methodology: “NASS is obligated to withhold, under Title 7, U.S. Code, any total that would reveal an individualâĂŹs information or allow it to be closely estimated by the public. Farm counts are not considered sensitive and are not subject to disclosure controls” (USDA NASS, 2017)

[14] Estimated marginal effects are computed by taking the exponential of the coefficient and subtracting one, i.e. $e^{\beta_i} - 1$.

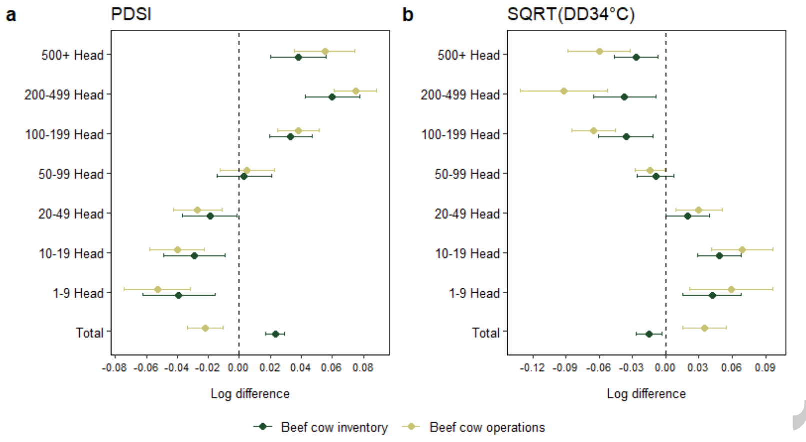

Figure 5. Marginal Effects of Climate Measures on Beef Cow Operations and Inventories

Notes: Estimated marginal effects generated by the seemingly-unrelated-regression (SUR) system of equations. Figure 5(a) shows the log difference in beef cow operations and inventories due to a one unit increase in the recent historical PDSI. Figure 5(b) shows the log difference in beef cow operations and inventories due to a one unit increase in the square root of the recent historical degree-days over 34°C ($\sqrt{DD34C}$).

Table 2. SUR Model of Beef Cow Operations by Herd Size

	Dependent variable: Log of beef cow operations							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Total	1-9 head	10-19 head	20-49 head	50-99 head	100-199 head	200-499 head	500+ head
PDSI	-0.022***	-0.053***	-0.040***	-0.027***	0.005	0.038***	0.075***	0.055***
	(0.006)	(0.011)	(0.009)	(0.008)	(0.009)	(0.007)	(0.007)	(0.010)
Log cattle hay price ratio	0.026	-0.129	-0.015	0.107*	0.300***	0.311***	0.258**	0.038
	(0.061)	(0.112)	(0.075)	(0.064)	(0.060)	(0.088)	(0.115)	(0.108)
Constant	0.164***	-0.255***	0.148**	0.328***	0.456***	0.341***	0.114**	-0.015
	(0.051)	(0.078)	(0.069)	(0.058)	(0.047)	(0.034)	(0.046)	(0.073)
County fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,659	9,659	9,659	9,659	9,659	9,659	9,659	9,659
Counties	1,171	1,171	1,171	1,171	1,171	1,171	1,171	1,171
R-squared	0.29	0.11	0.20	0.36	0.38	0.17	0.08	0.06

Notes: . *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the state level shown in parentheses.

of farms move in and out of this size category when recent climate conditions change. All other point estimates in 2 for the PDSI variable are significant at the 0.01 level.

These results are confirmed by those shown in Table 3, using climate measures that dis-aggregate heat and precipitation. Average grazing-season degree-days over 34°C is positively related with the total number of beef cow operations and significant at the 0.01 level. Computed at the median, one additional heating degree-day is associated with a 0.8% increase in the total number of cow-calf operations. Looking again across size classes, exposure to extreme heat is positively related to the number of small operations and negatively related to the number of large operations, though

Table 3. SUR Model of Beef Cow Operations by Herd Size

	Dependent variable: Log of beef cow operations							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Total	1-9 head	10-19 head	20-49 head	50-99 head	100-199 head	200-499 head	500+ head
$\sqrt{DD34C}$	0.035***	0.059**	0.069***	0.030**	-0.014*	-0.065***	-0.092***	-0.060***
	(0.012)	(0.023)	(0.017)	(0.013)	(0.008)	(0.012)	(0.024)	(0.017)
Precipitation	-0.008	-0.019	-0.014	-0.012	-0.009	0.004	0.018*	0.029**
	(0.008)	(0.014)	(0.011)	(0.011)	(0.007)	(0.005)	(0.010)	(0.011)
Precipitation squared	0.0001	0.0001	0.0001	0.0001	0.0001**	-0.0000	-0.0001*	-0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Log cattle hay price ratio	0.033	-0.092	-0.019	0.073	0.260***	0.300***	0.312***	0.126
	(0.048)	(0.086)	(0.065)	(0.059)	(0.053)	(0.083)	(0.116)	(0.102)
Constant	0.052***	0.096***	0.124***	0.092***	0.043**	-0.048	-0.180***	-0.173***
	(0.016)	(0.025)	(0.022)	(0.020)	(0.021)	(0.033)	(0.038)	(0.038)
County fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,188	7,188	7,188	7,188	7,188	7,188	7,188	7,188
Counties	1,171	1,171	1,171	1,171	1,171	1,171	1,171	1,171
R-squared	0.24	0.06	0.16	0.30	0.32	0.15	0.07	0.07

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the state level shown in parentheses.

Table 4. SUR Model of Beef Cow Inventory by Herd Size

	Dependent variable: Log of beef cow inventory							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Total	1-9 head	10-19 head	20-49 head	50-99 head	100-199 head	200-499 head	500+ head
PDSI	0.023***	-0.039***	-0.029***	-0.019**	0.003	0.033***	0.060***	0.038***
	(0.003)	(0.012)	(0.010)	(0.009)	(0.009)	(0.007)	(0.009)	(0.009)
Log cattle hay price ratio	0.042	-0.104	-0.015	0.103	0.252***	0.297***	0.175	-0.098
	(0.055)	(0.105)	(0.069)	(0.070)	(0.076)	(0.097)	(0.134)	(0.069)
Constant	0.206***	-0.334***	0.037	0.243***	0.405***	0.365***	0.163***	0.024
	(0.025)	(0.053)	(0.049)	(0.049)	(0.048)	(0.037)	(0.050)	(0.060)
County fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,704	4,704	4,704	4,704	4,704	4,704	4,704	4,704
Counties	854	854	854	854	854	854	854	854
R-squared	0.18	0.11	0.12	0.31	0.39	0.23	0.08	0.05

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the state level shown in parentheses.

Table 5. SUR Model of Beef Cow Inventory by Herd Size

	Dependent variable: Log of beef cow inventory							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Total	1-9 head	10-19 head	20-49 head	50-99 head	100-199 head	200-499 head	500+ head
$\sqrt{DD34C}$	-0.015**	0.042***	0.048***	0.020*	-0.009	-0.036**	-0.037**	-0.027**
	(0.007)	(0.016)	(0.012)	(0.012)	(0.010)	(0.015)	(0.017)	(0.012)
Precipitation	0.013***	-0.020*	-0.013	-0.011	-0.005	0.009**	0.026***	0.022**
	(0.004)	(0.012)	(0.010)	(0.010)	(0.007)	(0.004)	(0.009)	(0.011)
Precipitation squared	-0.0001***	0.0001*	0.0001	0.0001*	0.0001	-0.0000	-0.0002***	-0.0002**
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Log cattle hay price ratio	0.118**	-0.092	-0.030	0.060	0.231***	0.327***	0.276**	-0.014
	(0.053)	(0.101)	(0.056)	(0.067)	(0.077)	(0.107)	(0.139)	(0.058)
Constant	-0.022	0.103***	0.105***	0.091***	0.068**	0.015	-0.083*	-0.127***
	(0.023)	(0.025)	(0.024)	(0.023)	(0.028)	(0.038)	(0.044)	(0.040)
County fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,319	3,319	3,319	3,319	3,319	3,319	3,319	3,319
Counties	854	854	854	854	854	854	854	854
R-squared	0.11	0.06	0.12	0.28	0.34	0.20	0.07	0.06

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the state level shown in parentheses.

statistical significance varies somewhat across equations. At the median, an additional degree-day over 34°C predicts a 1.3% decline in the number of farms with 500 or more head of beef cows (0.01 significance level). The same increase in heat exposure suggests an offsetting 1.3% increase in the number of farms with 1-9 head (0.05 significance level). The results in Table 3 indicate that the impact of heating degree-days is not linear across farm sizes. The coefficient on degree-days over 34°C is larger in magnitude and more statistically significant for farms with 10-19 head than for those with fewer than 10. Similarly, farms with between 100 and 499 head appear more affected by heating degree-days than the largest farms, though the coefficients for the 100-199 head and 500 plus head groups are not statistically different.

While precipitation does not have a statistical impact on the number of beef cattle operations overall, it is related to farm numbers in the largest size classes. Among farms with at least 200 head of beef cows, the relationship between rainfall and the number of operation follows a downward concave pattern. A one-cm increase in average grazing-season rainfall is associated with an expansion of operations in the 200-499 head group, up until about 90 cm (the 94th percentile for rainfall in our sample), after which additional rainfall is associated with a contraction in farms of this size. However, the coefficients on the precipitation variables are only significant at the 0.1 level. For farms with at least 500 head of beef cows, a negative response sets in at the much lower threshold of 72.5 cm (76th percentile). The precipitation and precipitation squared variables are also more significant for the 500 plus group at the 0.05 and 0.01 levels, respectively It may be that, at least for herds between 200 and 500 cows, the quadratic relationship modeled for precipitation is simply capturing the diminishing marginal benefits of rainfall. In the case of herds with 500 beef cows or more, however, a meaningful negative relationship is apparent for average precipitation in excess of about 73 cm. Our results suggest that rainfall patterns influence the herd sizes of the largest cattle farms, who may be more likely to grow perennial forages for sale off-farm.

Moving to Table 4, we find the same pattern for the inventory of beef cows across herd sizes, with the distribution of beef cattle shifting from larger to smaller operations during periods of drought. But unlike the results for beef cow operations, drought is negatively related to the overall number of beef cows in the county; the expected result of producers liquidating their herds in response to limited forage. Column (1) suggests that for every one-unit decrease in the average grazing-season

PDSI, a county's total beef cow herd contracts by about 2.3% (significant at the 0.01 level). The same change in the PDSI is associated with a 4% rise in the number of beef cows in the smallest herd size group and a nearly offsetting 3.9% decline among the largest herd size group, both of which are significant at the 0.01 level. Consistent with our farm estimates, the association is largest for herds with between 200 and 499 beef cows, which grow by 6.2% when the 5-year average PDSI increases by one unit. The estimated impact of the PDSI is null and insignificant among herds with 50-99 head. Where statistically meaningful associations are found, all are significant at the 0.01 level with the exception of the 20-49 head group (significant at the 0.05 level).

Results shown in Table 5 for DD34C and precipitation generally confirm the results based on the PDSI. The coefficient estimated for $\sqrt{DD34C}$ in the pooled regression is -0.015 and significant at the 0.05 level, suggesting that independent of precipitation, exposure to extreme heat is negatively related to the overall beef cow herd. For the median county, if the average number of degree-days over 34°C during the grazing season rises by one, the number of beef cows would be expected to fall by 0.3%. While the overall change is small, extreme temperature exposure is more economically important for the smallest and largest herd size groups. For herds of 1-9 head and 10-19 head, a one-unit increase DD34C is associated with a rise in the number of animals in those groups by about 1% (0.01 significance) at the median of the data. For operations with between 20 and 49 head, the association is half as large at 0.5% and only significant at the 0.1 level. The relationship between extreme heat and beef cow inventories turns negative at herds of 100 head or more. Cattle inventories decline by 0.8%, 0.9%, and 0.6% (all at the 0.05 significance level) for herds with at least 100, 200, and 500 beef cows, respectively. A T-test indicates that these estimates are not statistically different from one another.

Unlike our results for beef cow operations, we find that rainfall may affect the overall stock of beef cows. According to column (1) of Table 5, additional grazing-season precipitation is associated with expansion in the overall beef cow herd, until about 85 cm, after which excess rainfall is negatively related to total inventories (significant at the 0.01 level). The association between grazing-season precipitation and the number of beef cows is again most apparent in the largest herd sizes. Herds with between 200 and 500 beef cows grow as average rainfall increases, until about 88 cm, corresponding to the 93rd percentile for precipitation in our sample. The precipitation coefficients are significant at the 0.01 level for this group. Herds among farms with more than 500 beef cows peak at 71 cm of average precipitation (73rd percentile). These thresholds are very similar to those for the number of operations shown in columns (7) and (8) of Table 3 and are generally more statistically significant. For the smallest farms, rainfall is negatively related to cattle inventories. The number of beef cows in herds with fewer than 10 head falls as precipitation rises until about 100 cm of average rainfall, though the estimated impact is only significant at the 0.1 level.

Looking at the estimates for relative cattle prices across Tables 2-5, we see that significant supply responses are generally restricted to mid-size herds. There is no discernible effect on the number of cow-calf operations overall, seen in column (1) of Table 4. We do find a statistically significant association for beef cow inventories at the 0.05 level in Table 5, which is consistent with the expectation that the beef cattle inventory cycle follows the beef cattle price cycle and suggests an elasticity of about 0.12%. For herd size groups with between 50 and 499 beef cows, a 1% increase in the ratio of feeder calf prices to hay costs is estimated to increase the number of farms by between 0.26% and 0.31%. The same price increase is associated with a 0.23%-0.33% growth in the supply of beef cows. Where present, statistically significant estimates are mostly at the 0.01 level with some at the 0.05 level.

Surprisingly, relative profitability is not related to the number of farms or animals in the largest herd size category—those with 500 beef cows or more. The supply elasticities estimated for this group are both positive and negative, but small and statistically insignificant in all cases. The apparent null result among large operations is likely explained by the absence of an upper threshold for this size category. In some cases, operations in this category may undergo large changes but not transition between categories. It may also be explained, in part, by a higher propensity of these farms to sell feed off-farm, making high hay prices a cost to some farms and a source of revenue for others.

Robustness Checks

As mentioned in the description of our empirical approach, several data selection decisions were made in response to the presence of zero-valued and missing-valued observations. This is particularly true for the beef cow inventory models, which, due to non-disclosure policies by USDA NASS, leaves us with a sample size that is less than half that of the beef cow operations models. Here we summarize the results from multiple alternative estimators and specifications intended to address these data limitations. The results from these robustness checks can be found throughout the supplemental appendix to this paper.

To begin, we test the sensitivity of our results to the minimum beef cow inventory threshold applied in all of our main results. For a county-year observation to be included in our estimation sample, it must maintain an average of at least 10,000 beef cows across all years, with the intention of focusing on primarily cattle-dependent regions of the U.S. However, this cutoff ignores about 44% of the U.S. beef cow herd that are scattered across counties less dependent on cattle production. Lowering the minimum threshold to a 5,000 beef cows average, then removing the threshold entirely does not materially change the marginal effects reported in Tables 2-5.

However, our sample size is much less sensitive to changes in this minimum threshold than to the inclusion of counties based on the completeness of data across herd sizes—a requirement of our panel SUR model—and restriction to counties with non-zeros for all dependent variables—the result of using the natural log transformation. Due to non-disclosure efforts by USDA NASS, our estimation sample is restricted to only those that have non-missing and positive beef cattle values across all herd size classes. This introduces the possibility of bias in our estimators due to over-representation of counties with disproportionately large cattle operations in the 500 plus herd size group—the most likely category to be suppressed. We use several alternative approaches to address this issue.

First, we run separate panel fixed-effects regressions for each size-class equation, allowing for the maximum number of observations to be included in each of the respective equations. This produces results that are similar to our main findings, though the effect of degree-days over 34°C on total beef cow inventories becomes statistically insignificant. While this approach addresses lost observations due to missing values, it does not fully deal with zero values for farms and inventories arising from the log transformation of the dependent variables. To overcome this, we run a series of panel Poisson regressions following Hausman, Hall, and Griliches (1984) that capture the count nature of the dependent variables—the discrete number of operations and animals—without discarding zeros.

Results of the fixed-effects Poisson are entirely consistent with our SUR approach (and in many cases larger in magnitude), showing a 3% decrease in the net number of beef cow operations as the 5-year average PDSI improves. The same is true for exposure to DD43C, which increases the total number of beef cow farms by 1% at the median of the data. For the inventory numbers, which are most impacted by data suppression and zeros, the effects of climate again confirm our main results. The fixed-effects Poisson model suggests a 1.6% increase in a county's beef cow herd in response to a one unit rise in the 5-year average PDSI, slightly less than the 2.3% change estimated by our main SUR strategy.

Finally, there may be unobserved trends in the number of farms and cattle that are specific to each region of the county that may be correlated with local weather patterns. For example, local cattle prices may be heterogeneous over time—a phenomenon we do not control for using national feeder calf prices. A common set of year fixed-effects ignores these spatio-temporal impacts. As a robustness check of our main results, we estimate the above SUR using time trends unique to each state. The climate variables of interest show similar impacts on beef cattle operations and herds under this specification, though their coefficients fall slightly in magnitude.

Figures A3 and A4 in the appendix provide a visual comparison of the climate effects on cattle operations and inventories and their 95% confidence intervals across specifications. While there is some variation in the point estimates for the beef cow inventory models at the largest herd scale—a product of the large number of missing and zero values in this size class—the results presented in this paper are generally robust.

Discussion

Our results confirm that farms expand their herds when soil moisture conditions improve, tilting the distribution of beef production toward large operations and away from small farms. In times of drought and excessive heat this phenomenon is reversed; as producers liquidate their herds in response to scarce forage, the distribution of farms and animals shifts inward from large to small. The net increase in beef cows accompanied by a net decrease in beef cow farms we observe during wetter (positive values of the PDSI) and cooler (fewer degree-days over 34°C) periods shows a tendency toward consolidation under favorable grazing conditions. The net decrease in farm numbers implies that part of this shift is driven by larger farms absorbing more cows, and perhaps, in part, by fewer smaller operations choosing to own cows. These operations may instead raise other types of livestock, produce and sell hay to the larger operations, or lease out land. Conversely, prolonged drought and heat may force large-scale operations to shrink or sell out entirely, creating opportunities for existing farmers, or young and beginning farmers, who do not own cattle to buy at lower prices. This leads to a net increase in the number of beef cattle farms driven by a growth in small operations.

Average beef cow herd sizes are known to be sensitive to climate (Rodziewicz, Dice, and Cowley, 2023; Hrozencik, Perez-Quesada, and Bocinsky, 2024). But until now, this was understood to be driven by the number of cows that can be supported by a fixed number of farms. Our findings imply that climate impacts both the supply of cattle and the number of farms themselves. We show that improved grazing conditions lead to a smaller number of large-scale operations. These results are at odds with recent work by Lacy, Orazem, and Schneekloth (2023), who show that regions with poor weather tend to have larger farms, while optimal growing conditions support smaller farms. We consider the possible mechanisms at work here.

First, these forces may be explained by differences across herd size groups, particularly the degree to which farms specialize in commercial cattle production. Gillespie, Whitt, and Davis (2023) highlights these differences using similar herd size classifications to those used in this paper. Based on results from the Agricultural Resource Management Survey (ARMS), they show that producers with small herd sizes are significantly more dependent on off-farm income. For U.S. farms with between 20 and 50 beef cows (the smallest group identified in the ARMS), gross farm income averaged just over \$35,000 in 2018, which was far exceeded by an average off-farm income of over \$96,000. For farms with 500 or more beef cows, gross farm income in 2018 averaged over \$1 million. Similarly, 95% of operators with at least 500 cows are majority-farming vs. only 53% of operators with fewer than 50 cows. Large cow-calf operations are also more efficient. Average cost-per-cow for the largest herd size group is \$910, less than half that of farms with 20-49 cows, which have average costs of \$2,099 per cow. Operations with small herds, therefore, have less at stake when drought occurs or market conditions change in terms of total economic value and relative contribution to total household income as compared to those with larger herds.

Second, unlike the U.S. manufacturing sector, where the largest firms are the most resilient to extreme temperatures (Ponticelli, Xu, and Zeume, 2023), large cow-calf operations are found to be the most vulnerable to drought and heat. Given their specialization in cattle production, the contraction in farms and animals within the largest size classes is likely a profit-maximizing response to limited forage availability. These shifts in the number and size of beef cattle farms are significant in light of the declining size of the national beef herd that has taken place within the cow-calf sector over time.

Burke and Emerick (2016) raise the possibility of "selective exit." Applying their argument to the livestock sector, the most productive farmers could react to warming temperatures by exiting the industry altogether, leaving it smaller and less efficient. While they only find weak evidence for this hypothesis, it may be at work in cow-calf production. When large farms are sold, they may be split among multiple buyers or family members who wish to retain some control over the business. Larger farms might also sell their livestock assets while retaining ownership of the land resources and decide to change their business focus to hay production.

The loss of even one operation with a herd of more than 500 beef cows has significant implications for the local cattle market and the economy in which it operates. Many of these animals will be sold for slaughter but others, particularly young cows and heifers, may be sold locally to neighboring producers. Small farms appear to benefit from such a scenario, thanks to the initially depressed market for cull cows and replacement heifers. The net increase in cow-calf operations we see in times of drought could then be the product of a single failed commercial farm being replaced by multiple small beginning farms that inherit some of the leftover breeding stock. These new operations may even be the inheritors of an older operator who is forced to dissolve the business earlier than anticipated. If so, we may have identified a new avenue through which climate change may impact agriculture—the acceleration of farm transition.

Last, scale economies may help explain the connection between poor climate and the growth of small farms. Farms are able to enter and exit cow-calf production more easily than other agricultural sectors due to the relatively low fixed costs and barriers to entry (Gillespie, Whitt, and Davis, 2023). A wheat farm, for example, can incorporate a cow-calf enterprise into its existing operation without incurring the large infrastructure investment that would be required for hog or poultry production. Moreover, marketing contracts, common in other animal agriculture sectors, are not an impediment to new entrants in cattle production due to the vertically fragmented nature of the beef supply chain.

Collectively, these findings provide novel insights into climate adaptation within beef cattle production. We find evidence for two adaptation channels. The first takes place at the intensive margin where farms expand and contract by adjusting stocking rates to recent climatic conditions. At this margin, severe drought may alter the makeup of the local cattle industry, but will leave the overall number of farms unchanged. The second channel operates on the extensive margin. It involves farms choosing to enter or exit cattle production in response to weather patterns. For some large specialized cattle operations, farm exit may be the most immediate drought-adaptation choice available (Burke and Emerick, 2016), creating space for multiple smaller operations to add a beef cattle enterprise, if only temporarily. When conditions improve, the overall number of beef cattle farms shrink, possibly the result of small diversified operations converting to primarily crop production like hay or land leasing for grazing rather than owning livestock outright. At the same time large operations increase their breeding stock. Hornbeck (2012) finds that only a small share of farms responded to the Dust Bowl of the 1930s through land-use changes at the intensive margin. Adjustment mostly came in the form of farm exit and rural depopulation.

Conclusions

This paper seeks to understand the relationships between climate and consolidation within the cow-calf sector of the U.S. beef industry. Previous work has shown that large firms may be better equipped to adapt to climate change. Future warming may accelerate concentration in some industries as a disproportionate number of small firms exit and large firms expand. Using county-level data from the Census of Agriculture going back to 1974 and climate data from multiple sources, we estimate the impacts of drought, heating degree days, and precipitation on the number of beef cattle farms and inventories across herd size groups.

Our findings suggest that drought and extreme heat not only reduce average beef cow herd sizes in the United States through herd liquidation, but also by growing the number of small farms, changing the makeup of the industry. If severe enough, large drought-affected operations may exit the industry, opening opportunities for new entrants, hobbyists, or diversified crop operations that are less specialized. Far from accelerating industry consolidation in cattle production, drought and heat appears to deter it. Rather, to the extent that consolidation is present and considered a problem for the cow-calf sector, it appears during cool and wet periods which may allow large farms to expand and absorb smaller operations.

If extreme drought and temperature become more common in the cattle-producing regions of the U.S., large farms will become more vulnerable and may be more likely to downsize or fail. This has implications for rural communities where cattle producers live and work. The loss of breeding stock, or outright farm failure, directly affects input suppliers and local businesses, while changes in ranch scale may indirectly affect local economies by, for example, increasing farmers' reliance on off-farm income. Targeted interventions that prevent farm failure may be cost-effective relative to these total downstream impacts.

Risk management policies such as the Pasture, Rangeland, and Forage insurance program, which relies on a rainfall index, and the Livestock Forage Disaster Program (LFP), which is based on the U.S. Drought Monitor, should take into consideration the effects of drought on farms of different sizes and on the composition of the industry itself. Emergency haying and grazing of Conservation Reserve Program (CRP) acres during drought events may also consider how to target the most vulnerable regions or change eligibility requirements based on the composition of ranches in an area. Previous work has shown that government support for agriculture has distributional consequences (Lusk, 2017; Bekkerman, Belasco, and Smith, 2019), even leading to greater consolidation in some cases (Azzam, Walters, and Kaus, 2021). Interventions designed to support the cattle industry in the face of a warming climate should incorporate farm size as a factor.

Finally, a long-standing policy concern is the perceived market power of the highly concentrated meat processing sector over beef cattle producers (MacDonald et al., 2000; Lusk, Tonsor, and Schulz, 2021; McKendree, Saitone, and Schaefer, 2021; Saitone et al., 2023). Changes in the size distribution of cattle production due to future climate change may affect this relationship, with implications for producer welfare. Greater concentration in the upstream portion of the beef supply chain following extended cool and wet periods may give producers greater bargaining power over local buyers and suppliers, while severe drought may produce the opposite effect as production is spread more thinly across farms. However, concentration and market power are typically associated with firms reducing quantity to maintain high prices. Our results suggest that consolidation in the cow-calf sector coincides with an expansion in the total beef cow herd, leading to lower feeder cattle prices. Similarly, as drought distributes a smaller beef herd over more, but smaller, operations, any loss of bargaining power may be offset, at least in part, by high cattle prices.

Future research should explore the welfare impacts of drought resulting from structural changes throughout the beef supply chain, as well as the role of government policy in mitigating the impacts of climate change on cow-calf producers given the distributional impacts we observe. Using similar data, other research could compare the impacts of drought across size classes for other crop and livestock sectors (e.g. hogs, dairy cattle, beef cattle finishing) to those found here for cow-calf production.

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