Extreme Heat and Livestock Production: Cost and Adaptation in the US Dairy Sector

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Abstract

We quantify the impact of heat stress on the dairy industry throughout the Midwestern United States in the years 2012-2016 using animal-level production data. When temperature and humidity increase above critical levels, dairy cows become heat stressed and eat less which causes a drop in milk production. We estimate a total of $60 million in lost profit over a five year period. These losses are mostly due to moderate-intensity heat events, though we find the largest per-event losses following high-intensity events. Losses are largest on small farms, while large farms appear to mitigate the effects of low-intensity heat events. Crucially, certain types of dairy cattle are more susceptible than others: dairy cows that have given birth multiple times and are early in their production cycle are the most productive but also the most vulnerable to heat stress. We estimate that these cattle lose about between 3-6% of their milk production in a heat wave as opposed to at most 2% for other cattle. One low-cost form of adaption dairy farmers can use to mitigate these losses is changing the time of year that cattle can give birth. Using a back of the envelope calculation, we estimate that $21.54 million in lost profits could have been avoided in this period if all cows gave birth in the fall instead of the spring.

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1 Introduction

The dairy industry faces an impending challenge: increasingly frequent extreme heat events due to climate change (IPCC, 2022). Protecting livestock agriculture from the effects of climate change is a policy priority given that it is a high-value sector and contributes 40% of agricultural production in high-income countries and 20% in low-income countries (Food and Agriculture Organization of the United Nations, 2021).

The dairy industry is especially vulnerable to heat events since cattle experience "heat stress" at high levels of temperature and humidity. Heat stressed cattle eat less, which causes their milk productivity to drop in an extreme heat event (Key et al., 2014; St-Pierre et al., 2003; West et al., 2003). Losses in dairy production pose a threat to global food security, as dairy is a low-cost protein source for smallholder farmers and low-income populations worldwide (Tricarico et al., 2020). Moreover, dairy products are an important source of key nutrients (e.g., calcium, vitamins B12 and B5, and magnesium) for vulnerable groups like pregnant women and children (Tricarico et al., 2020).

The impacts of heat stress on dairy industry production has either been quantified using state-level data (Gisbert-Queral et al., 2021; St-Pierre et al., 2003) or using farm-level data from a limited number of herds (Bohmanova et al., 2007; Key et al., 2014). These types of data have two shortcomings. First, production data aggregated to the farm- or state-level hide an important determinant of heat stress: the timing of each cow's production cycle. Dairy cows will experience larger drops in milk production if they give birth in the spring as opposed to the fall because their most vulnerable period, right after they give birth, will coincide with the hottest part of the year. Dairy farms can decide to change when cows give birth to mitigate heat stress, but this form of adaptation is not possible to detect when production data is aggregated. A second shortcoming of previous studies is that production data are almost always aggregated to the monthly or annual level. Without a daily measure of milk production, it is difficult to understand the precise impacts of heat waves on milk production.

Our research fills these gaps by studying the short-run impacts of heat stress and how patterns in calving dates mitigate the damages from heat stress. We pair panel data on cow-level milk production collected every month for about 18,000 dairy farms throughout the Midwestern United States with daily temperature and humidity data. We find total losses for herds in our sample over the period are equivalent to 0.5% of the total dairy industry's profits in each year. In total, we estimate that the herds in our sample lost 975 million gallons of energy-adjusted milk and $60 million in profit over five years due to heat stress. Dairy cattle experience heat stress at THI levels above 72 THI (Armstrong, 1994). We find minimal losses due to low-stress events equivalent to 72 - 80 THI, despite evidence in the dairy science literature that even low-stress events affect milk yield. This suggests that farmers have already adopted management methods to mitigate low-stress days.

Our novel data allows us to produce the first large-scale estimates of how the effects of heat stress vary over a cow's year-long production cycle. We find that heat stress vulnerability coincides with the most productive phases in a cow's lactation cycle, specifically cows that have given birth more than once and have given birth in the past four months. These cows experience a 2% drop in milk production in low stress, 4% drop on medium-stress days and a 6% drop under extreme stress conditions. In comparison, cows giving birth for the first time or that are in the last 6 months of their cycle experience at most a 2% drop in milk production from a single extreme heat event. We conclude by estimating the impact of a heat wave for each state individually and see evidence that states with more cows giving birth in the spring see larger heat stress impacts.

Our results have significant implications for understanding the impact of heat stress and adaption in the US dairy sector. First, the observed impacts of heat stress depend on where cows are in their production cycle. Because cows are most productive and vulnerable to heat stress early in their cycle, heat stress is less likely to appear significant in aggregated data if farms have already changed their calving dates. This leads to a second implication: farms can mitigate the economic damage from heat stress by simply changing the timing of their breeding decisions. Using our calculated heat stress impacts, we estimate a counterfactual where all cows that were early in their cycle during the summer months (May to August) were instead moved to a calving cycle that avoided these months (e.g., September or October). We estimate that $22.69 million worth of lost profit, about 37% of the total damages, could be avoided if older cows gave birth in the fall instead of the spring.

The paper proceeds as follows: section 2 gives background on the literature on heat stress. Section 3 describes our methods. Section 4 presents our results, and section 5 concludes.

2 Background

Heat stress impacts both the production ability and health of dairy cattle. At high levels of temperature and humidity, cattle experience an increase in their body temperature which causes them to eat less (West et al., 2003). The milk production ability of dairy cattle begins to decrease when the Temperature Humidity Index (THI) goes above 72 (Bohmanova et al., 2007; West, 2003). Ravagnolo et al. (2000) finds that, for each unit increase above 72, milk production drops about 1%. Heat stress also makes it more difficult for cows to become pregnant (Jordan, 2003). Each additional day a cow is not able to become pregnant costs the dairy operation $2.50 per cow due to lost production in the next production cycle (St-Pierre et al., 2003). Finally, heat stress also weakens a dairy cow's immune system and makes them more vulnerable to disease and early mortality (Bagath et al., 2019; Bishop-Williams et al., 2015).

Dairy producers have options to mitigate heat stress by changing day-to-day production practices, investing in cooling systems, and changing the timing of breeding decisions. Within a cow's production cycle, farms can change the timing of feeding and rest to avoid additional movement or metabolic processing at the warmest parts of the day. Farms can also make capital investments into shade, fans, and sprinklers that cool cattle down during heat waves (Key et al., 2014; Armstrong, 1994). These capital investments vary in their cost-effectiveness. Using a simulation model, St-Pierre et al. (2003) calculates that optimum heat abatement could reduce heat stress costs from all livestock industries by about $700 million. However, Gunn et al. (2019) finds that heat abatement is only cost-effective in the most intense heat waves. An arguably less-costly heat abatement strategy for some producers is to change the timing of their management decisions. Skidmore (2022) finds that Brazilian cattle ranchers sell cattle early to avoid having to raise cattle during the dry season. Even more relevant to the dairy industry is Ferreira et al. (2016) which uses a simulation model to show that cows about to give birth are the most vulnerable to heat stress. This suggests that changing the timing of when cows give birth is another way for dairy farms to mitigate heat stress.

A number of studies have attempted to quantify the impacts of heat stress on the dairy industry using small-sample on-farm data or aggregated, state-level data. Mukherjee et al. (2013), Qi et al. (2015), and Key et al. (2014) use stochastic frontier analysis to examine the impact of THI on the efficiency frontier of dairy farms throughout the country. In 100 farms in Florida and Georgia, higher THI was associated with less efficiency and investments in cooling systems were associated with higher efficiency (Mukherjee et al., 2013). Key et al. (2014) is the most expansive study, using data from the Agricultural Resource Management Survey (ARMS) from 2005 and 2010, and finds a similar, negative relationship between THI and dairy farm efficiency. Njuki et al. (2020) uses a sample of Wisconsin dairy farms and calculates that the cost of heat abatement depresses productivity growth in dairy by about 0.3%. In terms of adaptation, Gisbert-Queral et al. (2021) uses state-level data in the US from 1981 to 2018 and finds that sensitivity to extreme THI was lower in 2018 than in 1981, supporting the idea that the dairy industry has adapted to extreme climate shocks over the past few decades.

Our work makes two contributions. First, our work uses observational animal-level data, which can estimate a far more precise heat-stress impact than previous studies using farm- and state-level data. Vulnerability to heat stress depends on where a cow is in its production cycle, and the calculated impacts of heat stress can depend greatly on when observations are taken (Ferreira et al., 2016). We also have measures of one-day milk yield, measured monthly, and daily data on heat events so we can understand the precise impact of a heat stress event when it happens. The majority of studies have annual data

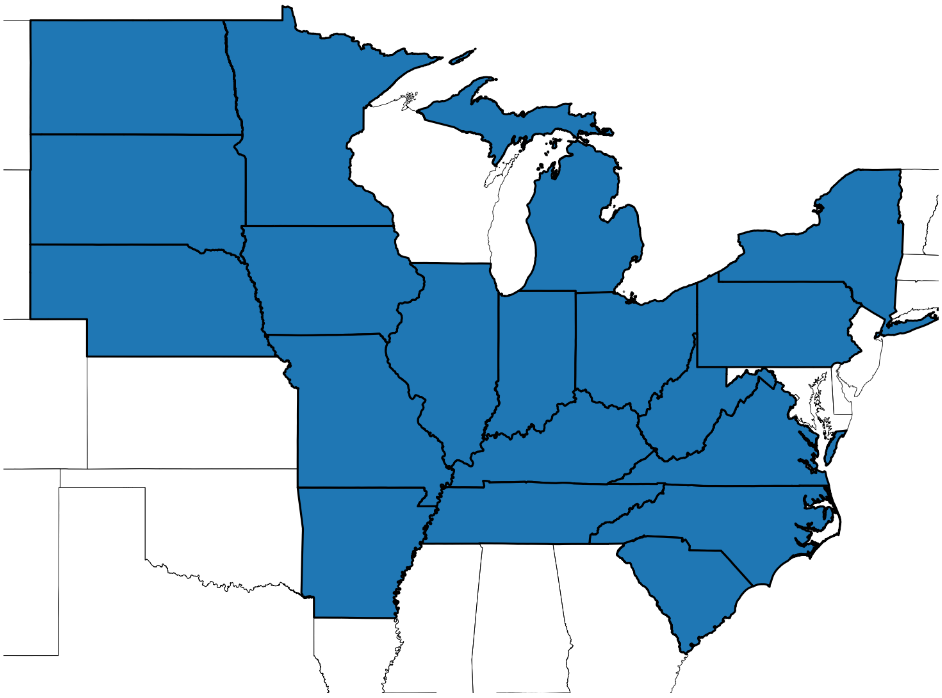


Figure 1: States with representative data in DRMS

on milk production and have to make assumptions about how a year's exposure to heat will translate into the sum of production for that year. Having a single-day reading of the cow's production every month allows us to bypass these assumptions by estimating the heat stress impacts for different cohorts of cattle. Our second contribution is that we can examine how calving patterns impact heat stress. A straightforward way for dairy farms to mitigate heat stress is by changing the timing of their breeding decisions so that cows do not experience during their most vulnerable periods, specifically the first 120 days of their lactation. Previous studies have focused only on capital investments and have overlooked changing breeding decisions as a cheap and effective method of adaptation.

3 Methods

3.1 Data

Dairy production data comes from Dairy Records Management Systems (DRMS), a cooperative that tracks dairy production on herds that are members of a Dairy Herd Improvement Association (DHIA). We use 56 million dairy cow production records sourced from over 18 thousand dairy farms from the years 2012 to 2016. Each farm's cows are sampled monthly, so the data are a panel of daily cow-level production for each farm that is a DHIA member. Our sample for this analysis covers the states in

Figure 1. About 44% of dairy farms nationwide are members of DHIAs and in our chosen states DHIA participation is about 50% (Council on Dairy Cattle Breeding, 2023). This sample also allows for a more comparable production system across states, as the states in this region have similar sized dairy farms and similar climates.

Daily weather data comes from gridMET, which measures temperature and humidity at the 1/24th degree (4-km grid) level (Abatzoglou, 2013). We process these to daily, county-level maximum and minimum temperature humidity index (THI) measurements. THI has been shown to be the best measure of the stress a cow experiences, as the combination of heat and humidity limits the cow's ability to cool through sweating or other forms of evaporative cooling (Armstrong, 1994; Bohmanova et al., 2007).[1] Cattle are even more negatively impacted when THI stays high during the day since they are even less able to cool off.

To incorporate not just the THI max but the amount of time spent above a cow's critical THI threshhold (about 72), we use THI heat load as our measure of heat exposure (St-Pierre et al., 2003; Key et al., 2014). THI heat load is calculated using the daily min and max of THI and modeling changes in THI throughout the day with a sine curve (see Figure A1 for a visual depiction). THI heat load measures the area under the sine curve but above the THI threshhold, which increases when both THI min and max increase. This measure is often used in the literature to account for days where there is a lower THI max but still prolonged exposure to heat because of a high THI min. Appendix A contains more information about the calculation of THI heat load and the relationship between heat load and our daily THI min and max readings.

We primarily use a measure of heat load that is discretized into quartiles of days with a non-zero heat load: (0 - 35], (35 - 70], (70 - 140] and 140 or above. Non-zero heat loads below 70 are roughly equivalent to low-stress days where THI max is between 72 and 80 (Appendix Figure A2).[2] Similarly, days with a heat load between 70 and 140 are usually equivalent to moderate-stress days where THI max is between 80 and 90. Days with heat load above 140 are usually days where THI max is above 90, which is often considered an extreme-stress day.

Figure 2 shows the distribution of heat load in the summer months (defined as May to September) of our sample. About 30% of days have zero heat load as THI max never crosses the 72 threshholds. Between 15 and 20% of days reach low levels of heat stress (non-zero heat laods below 70) and the remaining 15 and 20% of days reach moderate (70-140) and extreme (above 14) heat loads, respectively.

[1]We use the formula for THI from Mader et al. (2006) which is $THI = .8T + RH \times (T - 14.3) + 46.4$ where T is air temperature in degrees Celsius and RH is relative humidity between 0 and 1.

[2]Armstrong (1994) and subsequent papers defined categories based on the maximum THI on the day. Using this metric, they divided days into categories of 72 - 80 THI (low stress), 80 - 90 THI (medium stress) and 90 and above THI (extreme stress) based on the severity of the heat stress response in each of the categories.

Figure 2: Heat load distribution in summer months

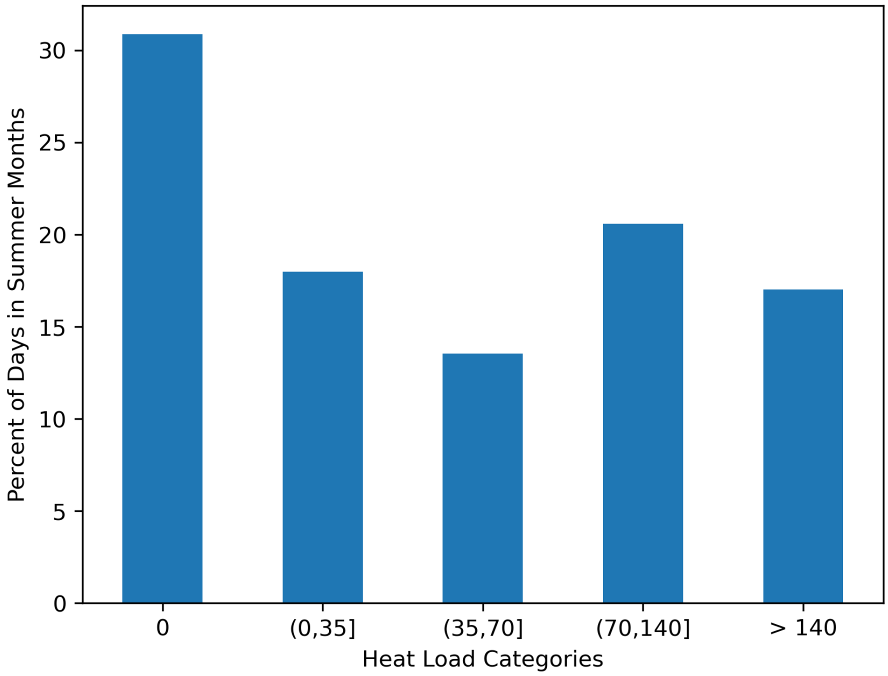


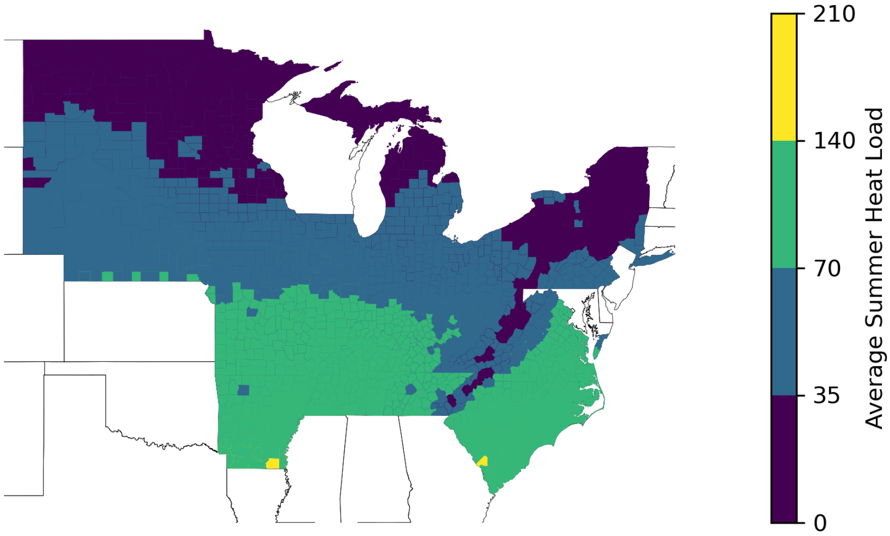
Figure 3 panel a shows the average heat load during summer across our sample and which quartile each county falls in. Almost all of New York, Minnesota, and North Dakota have a low heat load, with averages between 0 and 35. Midwestern states such as Iowa and Ohio experience average heat loads between 35 and 70. With the exception of the Appalachian mountain region, most southern states and parts of Iowa, Illinois, and Indiana, have a moderate average heat load during the summer.

Panel b of Figure 3 shows the number of days of extreme (> 140) heat load a county experiences across the five summer months, on average over the sample period. Most parts of the country experience at least 30 days of extreme heat load, while states like Missouri and South Carolina experience close to three months (90 days) of extreme heat load. We map the total extreme heat days in a county by year in Figure 4. We find that 2012 is the hottest year in our sample and is 2014 the coolest year. There is significant variation in heat load across our states and across the years in the sample.

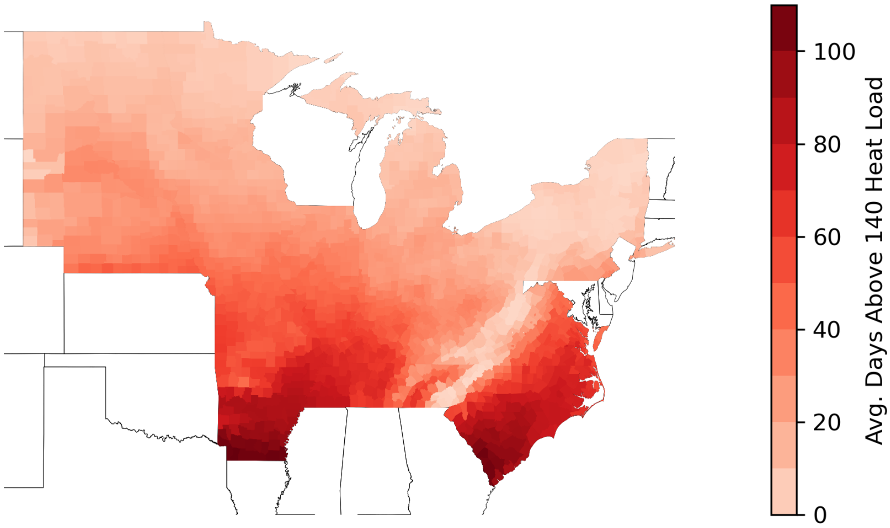
3.2 Empirical Strategy

Our goal is to estimate the impact of heat stress days on the daily milk production of individual cattle. A cow's production on a given day is explained by her physical environment, management and inputs, and where the cow is in its production cycle.

The relationship of daily milk production to the days since the cow gave birth (called "days in milk" or DIM) is modeled in a lactation curve. Figure 5 shows the shape of the lactation curve. Milk production

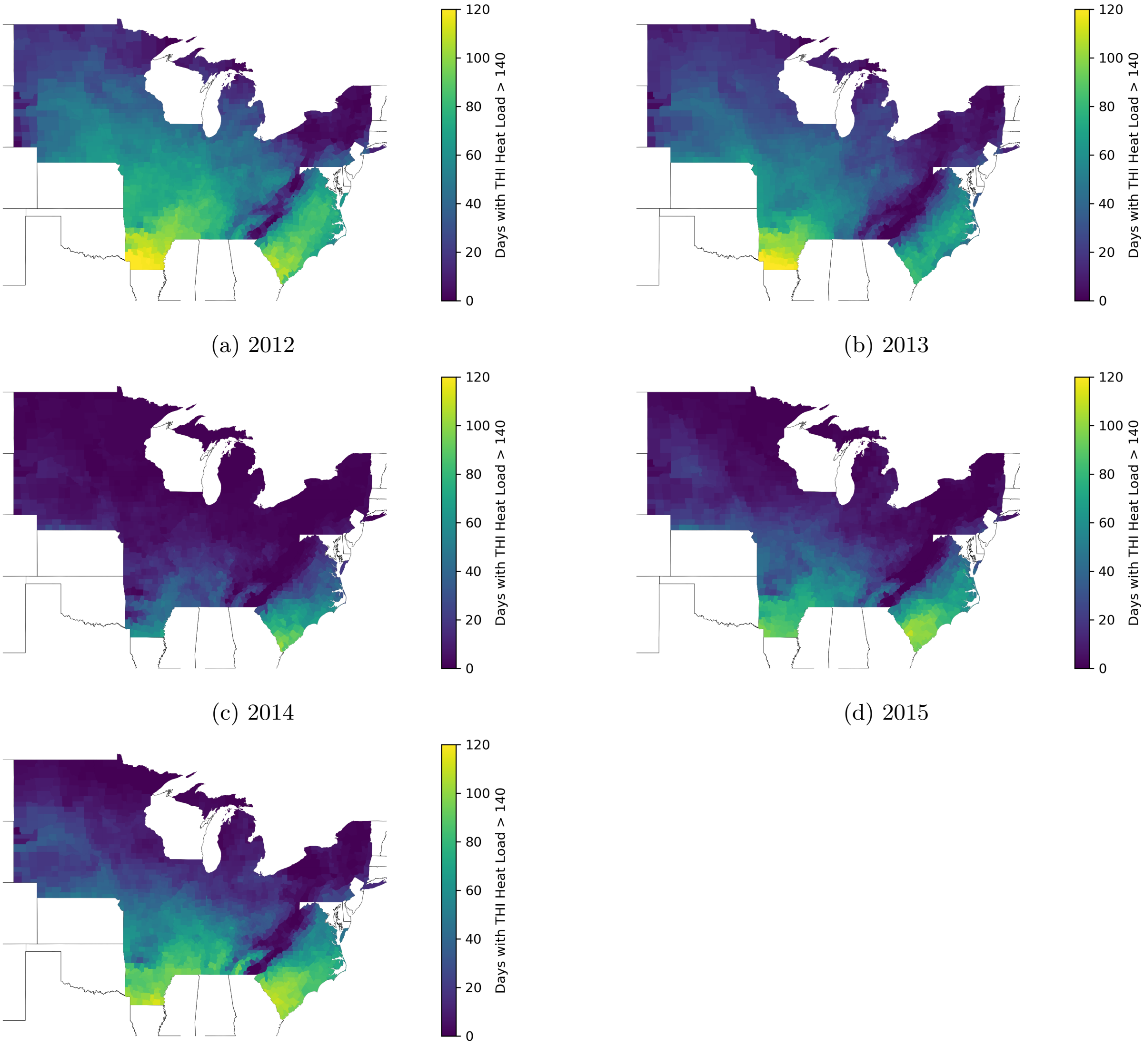


(a) Average summer heat load



(b) Number of days above 140 heat load in the summer

Figure 3: Heat load patterns across sample states



(a) 2012

(b) 2013

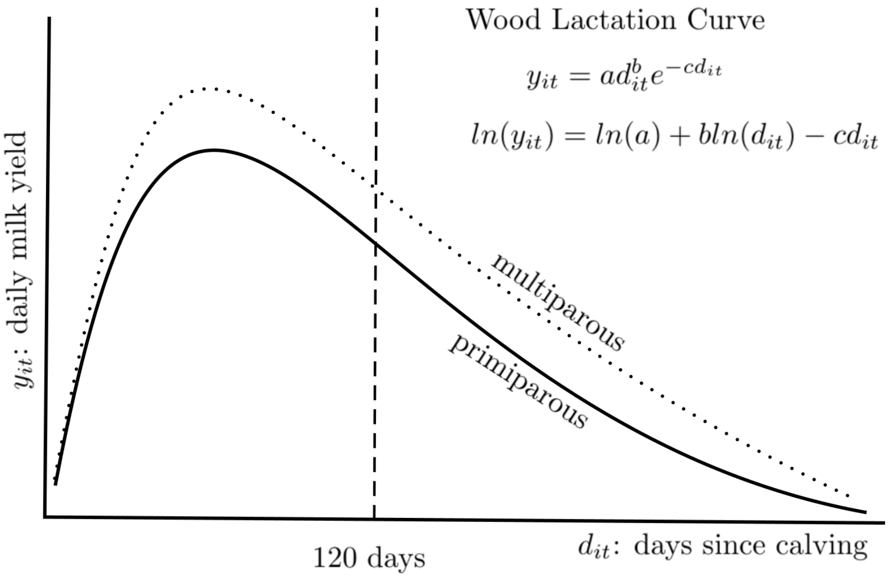
(c) 2014

(d) 2015

(e) 2016

Figure 4: Total extreme heat load (> 140) days per county per year, 2012 - 2016

Figure 5: Lactation curve and the Wood model



reaches its peak in the first 120 days of a cow's production cycle and is higher at every point for cows that have given birth multiple times, or cows that are "multiparous" (as opposed to primiparous cows that have only given birth once). The lactation curve is usually modeled mathematically as a half-gamma curve: $y = ad^{b}e^{-cd}$. Daily milk production is captured in y, d is days since calving, and a, b, and c are parameters of the curve. By taking the natural logarithm of both sides, the log of milk production is linear in d and $ln(d)$: $ln(y) = a + bln(d) - cd$. This model is referred to as the "Wood model" (Wood, 1967).

To explore the heterogeneous impacts of heat stress, we consider four categories: primiparous cows before 120 days, primiparous cows after 120 days, multiparous cows before 120 days, and multiparous cows after 120 days. We expect that multiparous cows before 120 days will be the most vulnerable to heat stress as these cattle are devoting the most energy into milk production.

Following Hutchins and Hueth (2021), we adapt the Wood model to incorporate heat stress and estimate how heat stress causes deviations of milk production from the biological lactation curve. To estimate the average impacts of heat stress across all cattle, we use the following specification:

$$ln(y_{ihct}) = f(d_{ihct}, l_{ihct}) + \sum_{p\in\mathbf{P}}\sum_{k=0}^{K}\beta_{pk}\mathbb{1}\{z_{c,t-k} \in P\} + \alpha_h + \gamma_t + \epsilon_{ihct}. \tag{1}$$

Our outcome, $ln(y_{ihct})$ measures the log milk production for cow i in herd h and county c at time t. We include the main factors from the Wood model interacted with the number of production cycles the cow has been through: $f(d_{ihct}, l_{ihct}) = l_{it} + bln(d_{it}) - cd_{it}$ where l_{it} is the number of production cycles the cow has experienced (i.e., 1 indicates that the cow is in their first production cycle) and d_{it} is days in milk. Our treatment is a series of dummy variables, $z_{c,t-k}$. Each dummy represents a range of values of THI heat load: (0 - 35), [35 - 70), [70 - 140) and 140 or more. We omit the base category of days with no heat load. We control for time-invariant herd characteristics (α_h) and month, year, and calving month fixed effects (γ_t). We cluster standard errors at the herd level, as we anticipate that the effect of heat stress on production varies at the herd level with management practices.

Next, we consider the heterogeneous impacts of heat stress based on the cow's lactation cycle:

$$\begin{aligned}
ln(y_{ihct}) = & f(d_{ihct}, l_{ihct}) + \sum_{p \in \mathbf{P}} \sum_{k=0}^{K} \beta^0_{pk} \mathbb{1}\{z_{c,t-k} \in p\} \\
& + \sum_{p \in \mathbf{P}} \sum_{k=0}^{K} \beta^1_{pk} \mathbb{1}\{z_{c,t-k} \in p\} \times Multiparous_{ihct} \\
& + \sum_{p \in \mathbf{P}} \sum_{k=0}^{K} \beta^2_{pk} \mathbb{1}\{z_{c,t-k} \in p\} \times EarlyDIM_{ihct} \\
& + \sum_{p \in \mathbf{P}} \sum_{k=0}^{K} \beta^3_{pk} \mathbb{1}\{z_{c,t-k} \in p\} \times Multiparous_{ihct} \times EarlyDIM_{ihct} \\
& + \alpha_h + \gamma_t + \epsilon_{ihct}.
\end{aligned} \tag{2}$$

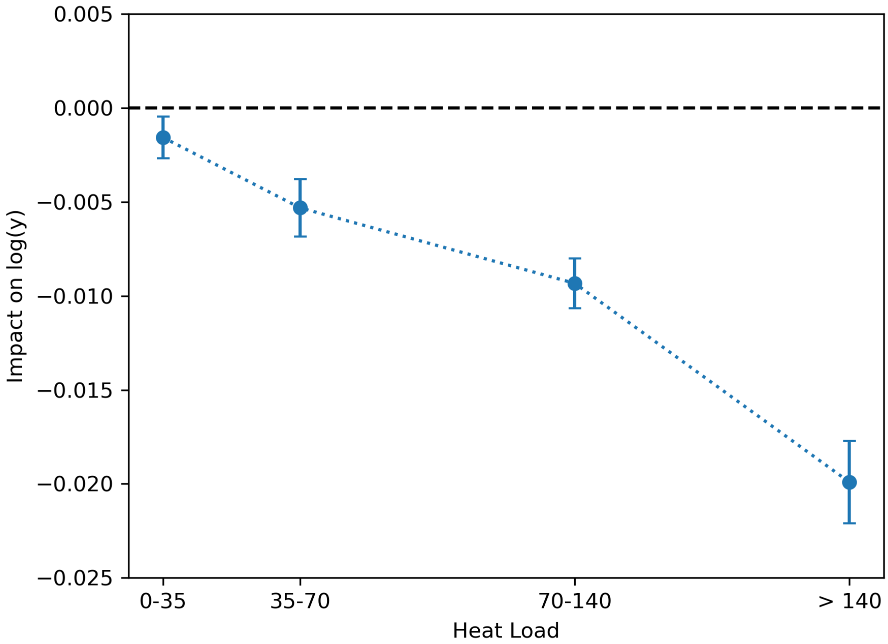
We interact heat stress events with two indicators: multiparous (i.e., $Multiparous_{ihct} = 1$ if the cow is not in her first lactation) and whether she is early in her lactation cycle (i.e., $EarlyDIM_{ihct} = 1$ if she is less than 120 days postpartum at time t.) By interacting heat stress events with these indicator variables we are testing whether different cohorts of dairy cattle respond differently to heat stress. The purpose of this specification is to determine the extent to which calving decisions determine the costs of heat stress. If there are no differences between these cohorts of cattle, then changing the timing of calving is not an effective method of mitigating heat stress. If significant differences exist, this would illustrate that producers can use calving decisions to buffer against heat stress.

4 Results

4.1 Heat Stress Impacts

We first estimate the average cost of heat stress across all cows in our sample. These results are similar to previous results in the literature, as they do not account for heterogeneous effects based on the cow's characteristics. Concurring with the literature, we find that milk yield falls due to heat stress and the

Figure 6: Average, non-linear impact of heat load

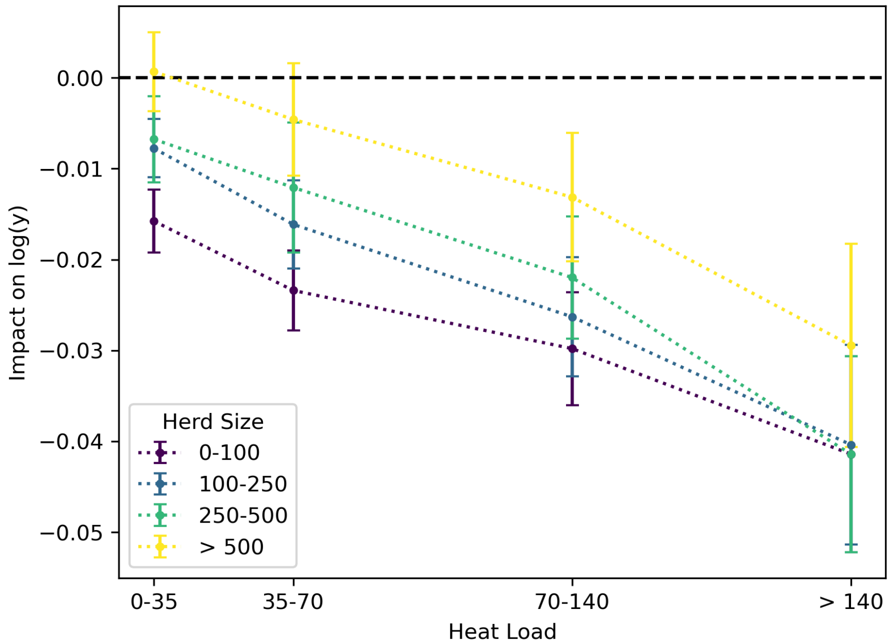


effects persist or even increase beyond the day of the heat event. Figure 6 shows the impact of different levels of heat load on milk production. Low levels of heat load (i.e., positive load under 70) reduce milk production at most by .5% on average while moderate levels of heat load (i.e., 70 - 140) double the effect to 1%. Extreme heat loads (i.e., over 140), however, double the effect to a 2% reduction in milk yield. These measured impacts are somewhat smaller than others found in the literature, which suggests some adaptation to heat stress has already taken place on these dairy farms.

Figure 7 shows how heat load impacts differ across herd sizes. We expect that larger dairy farms may have more resources to invest in machinery such as fans and sprinklers and should be the least impacted by heat stress. Our estimates confirm this. The effects of heat load are decreasing in herd size, and the largest dairy farms, those above five-hundred cows, experience no damages from low levels of heat load. All herd sizes experience significant drops in milk yield when heat load exceeds 70, although the smallest herds still experience a significantly higher loss than the largest herds. For days above 140, the size of the effects is statistically indistinguishable across herd size: all farm types experience between 2 and 4% drops in milk yield. This demonstrates that even large farms in our sample are not able to mitigate the most extreme heat stress.

Table 1 shows the impact of the heat load up to a week after the event. We find significant coefficients on longer lags; heat events as far out as eight days (Lag = 7) can have a significant effect on current-day milk production. Coefficients are consistently negative in all specifications, and some lags have significant impacts on milk yield at all levels of heat stress. Losses range from 0.2% in the week after a day with a

Figure 7: Impact of heat load across herd size



heat load less than 35, 0.2 - 0.4% losses after a heat load from 35 - 70, 0.3 - 0.8% after a heat load from 70 -140 heat load, and 0.5 - 2.0% losses after a heat load higher than 140. Because lags enter the model separately, these estimates do not incorporate the non-linear impacts of consecutive stress days. This may in part explain why we estimate a stronger impact of later lags; these lags would capture production later in a heat wave.

Next, we examine the impacts of heat stress on different cohorts of dairy cattle. Table 2 reports the main effect of heat stress and each interaction effect of heat stress with dummy variables for the cow's lactation cycle. Figure 8 shows the total effect of heat stress for each cohort of cows at varying levels of heat load.

The highest-yield cows, those with multiple births ("Multi") and that are less than 120 days post-birth ("Early"), experience the highest losses due to heat stress. These cows lose 3% of production even under low-stress conditions and up to 6% on a day with extreme stress. These multiparous cows see minimal losses or a very small bump in production (1% on a low stress day) when they are later in their cycle. In comparison, primiparous cows early in their cycle see a 1% reduction in milk yield regardless of heat load level. Later in their cycle, primiparous cows see losses that increase with heat load; they lose from 0.4% under low stress conditions to 2% under extreme stress conditions. These results indicate that the average effects of heat stress are largely driven by the most productive cows in each herd.

Table 1: Effects of heat load categories on log milk yield

Heat Load	Lag = 0
0-35	-0.001***
	(0.0005)
35-70	-0.005***
	(0.0007)
70-140	-0.009***
	(0.0006)
> 140	-0.0199***
	(0.001)
Observations	56,629,430
Adj. R^2	0.409

Heat Load	Lag = 0	Lag = 1	Lag = 2
0-35	-0.001	-0.0001	-0.003^{***}
	(0.001)	(0.001)	(0.001)
35-70	-0.003^{***}	-0.001	-0.005^{***}
	(0.001)	(0.001)	(0.001)
70-140	-0.004^{***}	-0.001	-0.010^{***}
	(0.001)	(0.001)	(0.001)
> 140	-0.009^{***}	-0.003^{*}	-0.023^{***}
	(0.001)	(0.002)	(0.001)
Observations	56,629,430		
Adj. R^2	0.409		

Heat Load	Lag = 0	Lag = 1	Lag = 2	Lag = 3	Lag = 4	Lag = 5	Lag = 6	Lag = 7
0-35	-0.001	-0.001	-0.002^{**}	-0.001	-0.002^{***}	-0.001	-0.0004	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
35-70	-0.002^{**}	-0.002^{*}	-0.002^{**}	-0.001	-0.003^{***}	-0.002^{**}	-0.002^{**}	-0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
70-140	-0.001	-0.002	-0.003^{***}	-0.001	-0.007^{***}	-0.005^{***}	-0.003^{***}	-0.008^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
> 140	-0.002	-0.002	-0.005^{***}	-0.005^{***}	-0.015^{***}	-0.013^{***}	-0.014^{***}	-0.020^{***}
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	56,629,430							
Adj. R^2	0.409							

Significance:	*p<0.1; **p<0.05; ***p<0.01
Covariates:	days in milk, log(days in milk), multiparous, somatic cell count
Fixed effects:	herd, month, calving month, year

Table 2: Effects of THI heat load, average and by lactation phase

	Ln(Milk Yield)			
	Average			
0-35	-0.002^{***}			
	(0.001)			
35-70	-0.005^{***}			
	(0.001)			
70-140	-0.009^{***}			
	(0.001)			
> 140	-0.020^{***}			
	(0.001)			
Observations	56,629,430			
Adj. R^2	0.409			
	Heat stress	Heat stress x Early DIM	Heat stress x Multiparous	Heat stress x Multiparous × Early DIM
0-35	-0.004^{***}	-0.011^{***}	0.014^{***}	-0.030^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
35-70	-0.007^{***}	-0.008^{***}	0.013^{***}	-0.037^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
70-140	-0.012^{***}	-0.004^{***}	0.015^{***}	-0.045^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
> 140	-0.020^{***}	0.002	0.011^{***}	-0.056^{***}
	(0.001)	(0.002)	(0.001)	(0.002)
Observations	56,629,430			
Adj. R^2	0.409			
Significance:	*p<0.1; **p<0.05; ***p<0.01			
Covariates:	days in milk, log(days in milk), multiparous, somatic cell count			
Fixed effects:	herd, month, calving month, year			

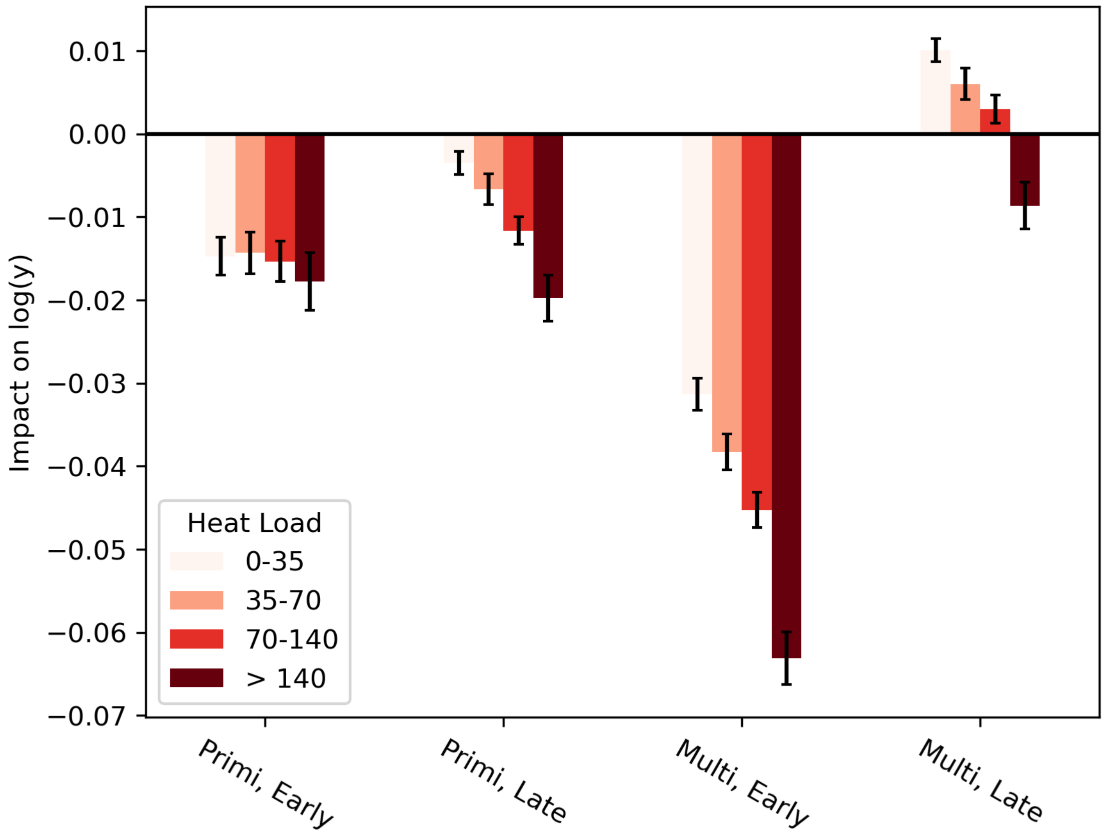
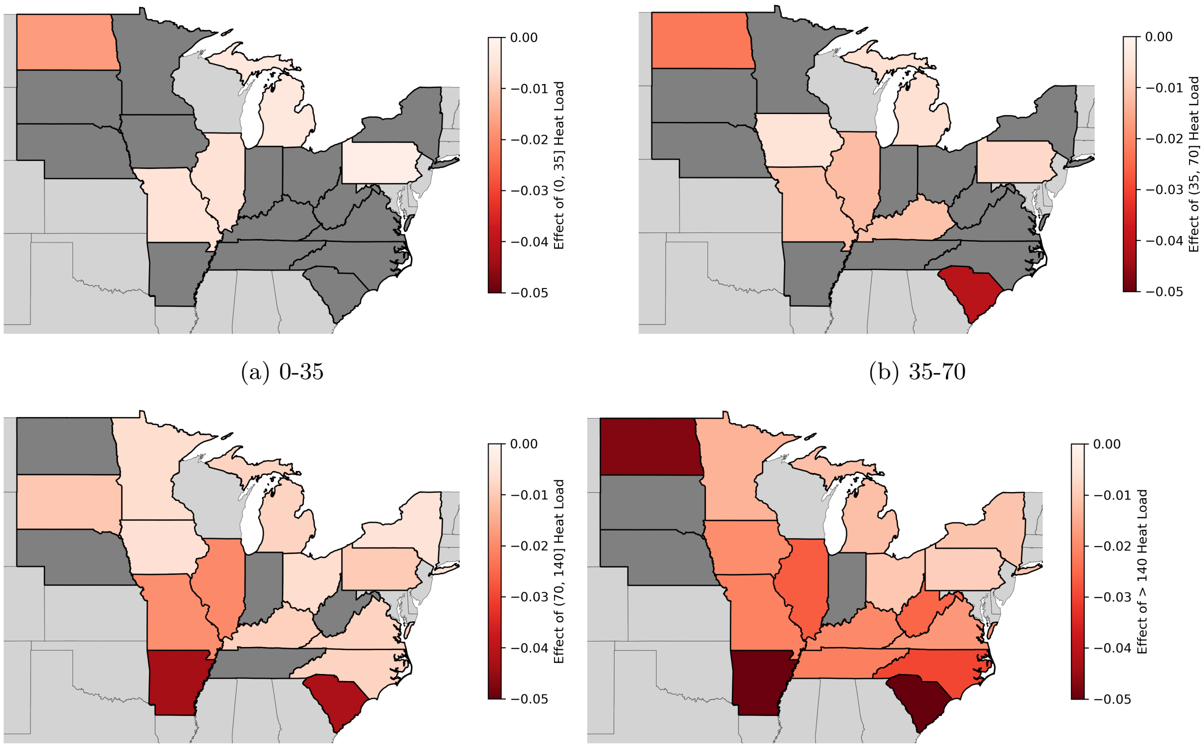


Figure 8: Effect of day-of heat load on milk yield



(a) 0-35

(b) 35-70

(c) 70-140

(d) > 140

Figure 9: State-level impacts of heat load

Note: states with coefficients not statistically different than zero at the 10% level are in gray.

4.2 Heat Stress and Calving Patterns Across States

Our results are not purely biological effects. Instead, they are the impacts of heat stress mitigated by management and capital investment made by farms to lessen heat stress. Since not all farms are equally exposed to heat stress, we would expect the impacts of heat stress to be different across the states in our sample. We finish our analysis by examining how heterogeneous the impacts of heat stress are across states and whether patterns in calving differ across states. If states with heat stress are shifting more births to the fall instead of the spring, this suggests that calving patterns may be changing in reaction to heat stress.

In Figure 9, we map the effect of each heat load category across states. Only a few states, North Dakota, Illinois, Missouri, Michigan, and Pennsylvania, experience significant losses in milk yield when heat load is between 0 and 35. As in our sample-wide estimates, we see increasing losses at higher levels of heat load. More states experience significant losses at 35 - 70 and 70 -140 heat load, and states' losses increase in magnitude as heat load increases.

States show different patterns of damage, which demonstrates the importance of management and adaptation. While nearly all states show an increase in losses as heat load increases, the increase is gradual and maximum losses are no more than 2% for some states (e.g., Michigan, Minnesota, and Pennsylvania). In these states, we expect that management practices are effective at mitigating heat stress at all levels of heat load. Notably, these are also relatively mild states. In contrast, some states do not experience any losses under low-stress conditions but high losses (up to 5%) under extreme stress conditions (e.g., Arkansas, North Carolina, South Carolina, and West Virginia). Farms in these states may have mitigated low-level heat load but are extremely vulnerable to high levels of heat load, which are common in these states. Notably, we do not detect significant losses at any heat load in Nebraska or Indiana; this warrants further study.

As we learned from our heterogeneous specification, the damages to a farm depend on where a cow is in their production cycle. This means that how resilient a state is to heat stress partly depends on when cows give birth in each state. How do calving patterns differ across states? In Figures 10 and 11, we graph the distribution of calving months (i.e., how many cows give birth in each month) and average number of extreme stress days per month by state.[3] We compare the percent of the herd that calves in a month to the percent that we would observe if calving were distributed randomly throughout the year: 8.3% per month.[4] The 8.3% per month rate is represented by the dashed, horizontal line.

We observe that disproportionately more cows give birth in fall months (i.e., after September) in states with more extreme summer temperatures. Arkansas, Tennessee, and South Carolina, experience an average of 20 or more extreme stress days in July; they also calves more than 12% of the annual total in September. In these warmest states, the fall births replace births in the summer months (i.e., May to August), all of which have birth rates of less than 7.5% of the annual total. In slightly milder states, Illinois, Indiana, Iowa, Kentucky, and Missouri all experience an average of 7.5 or more extreme stress days in July. These states still exhibit clear fall calving patterns; they calve at least 10% or more of the annual total in September and nearly that in October and November. These fall births replace births in March, April and May, all three of which fall below an 8.3% calving rate. We also observe more subtle versions of these patterns in Michigan, Minnesota, Ohio, all of which experience an average of 5 or fewer extreme heat days in August. These patterns suggest that some farmers are using the timing of calving to minimize losses from heat stress.

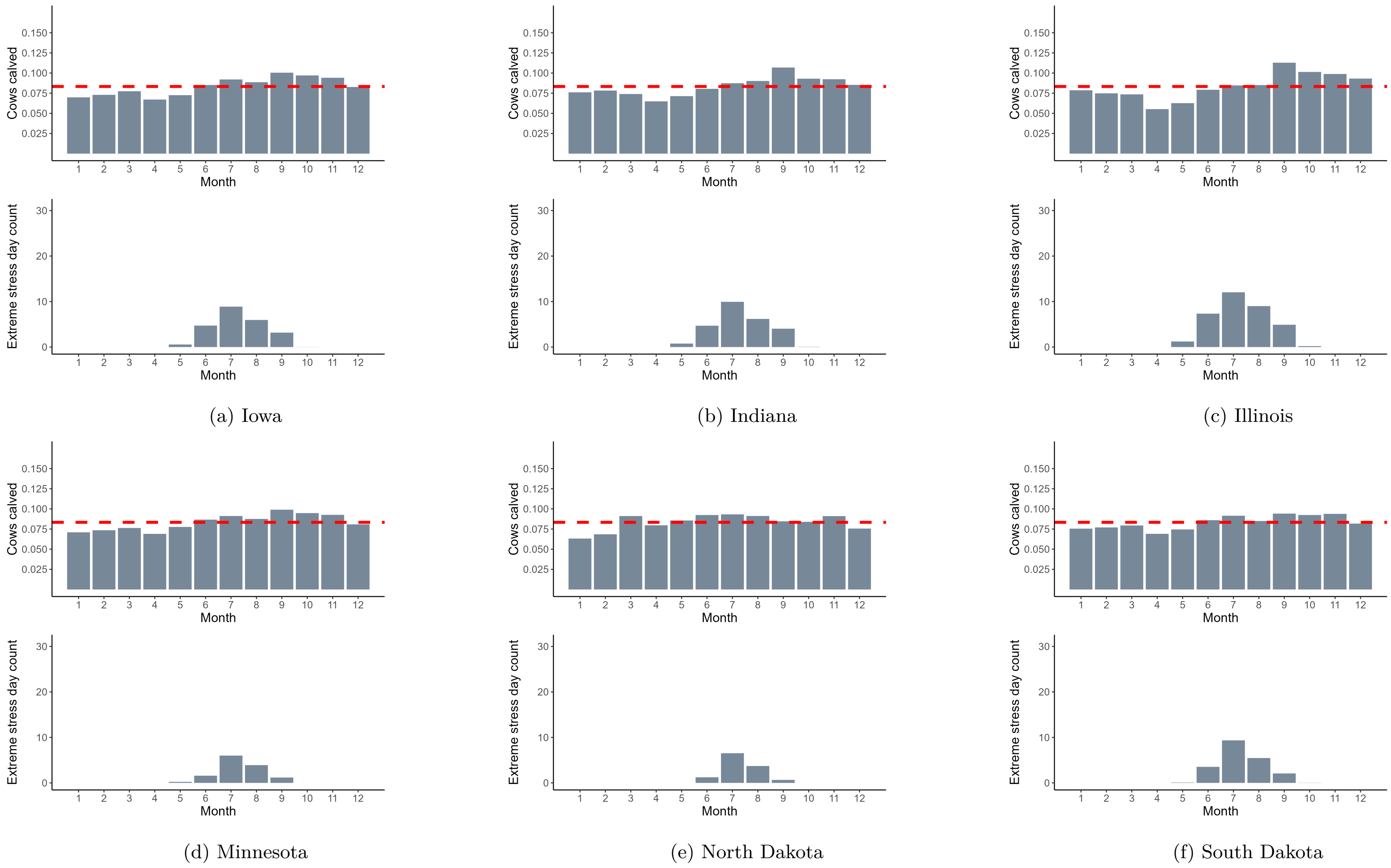
These patterns may in part also be driven by lower conception rates during heat events. Given a cow's ten month gestation, this could drive lower calving rates in the two months before hot months. For example, in South Carolina and Arkansas, where heat stress continues through the early fall, we see calving remains low through the summer months. In states where temperatures are high in the

[3]We estimate this average over the set of counties that have dairy cows.
[4]We normalize the number of births per month to a 30-day month.

summer but drop quickly in the fall months, we see the lowest rates of calving in April and May, with some rebound in the summer months. Future work should distinguish between attempted and successful insemination by heat stress at the time of insemination.

There are notable exceptions to these patterns. North Carolina experiences weather very similar to Kentucky, Tennessee, and Missouri, but it calves only 10% of the herd in September compared to 12.5% in these states. Calving in Virginia peaks in July and August, despite these being the hottest months of the year. In North Dakota, there is no evidence of fall calving; summer is the most common calving period in the state.

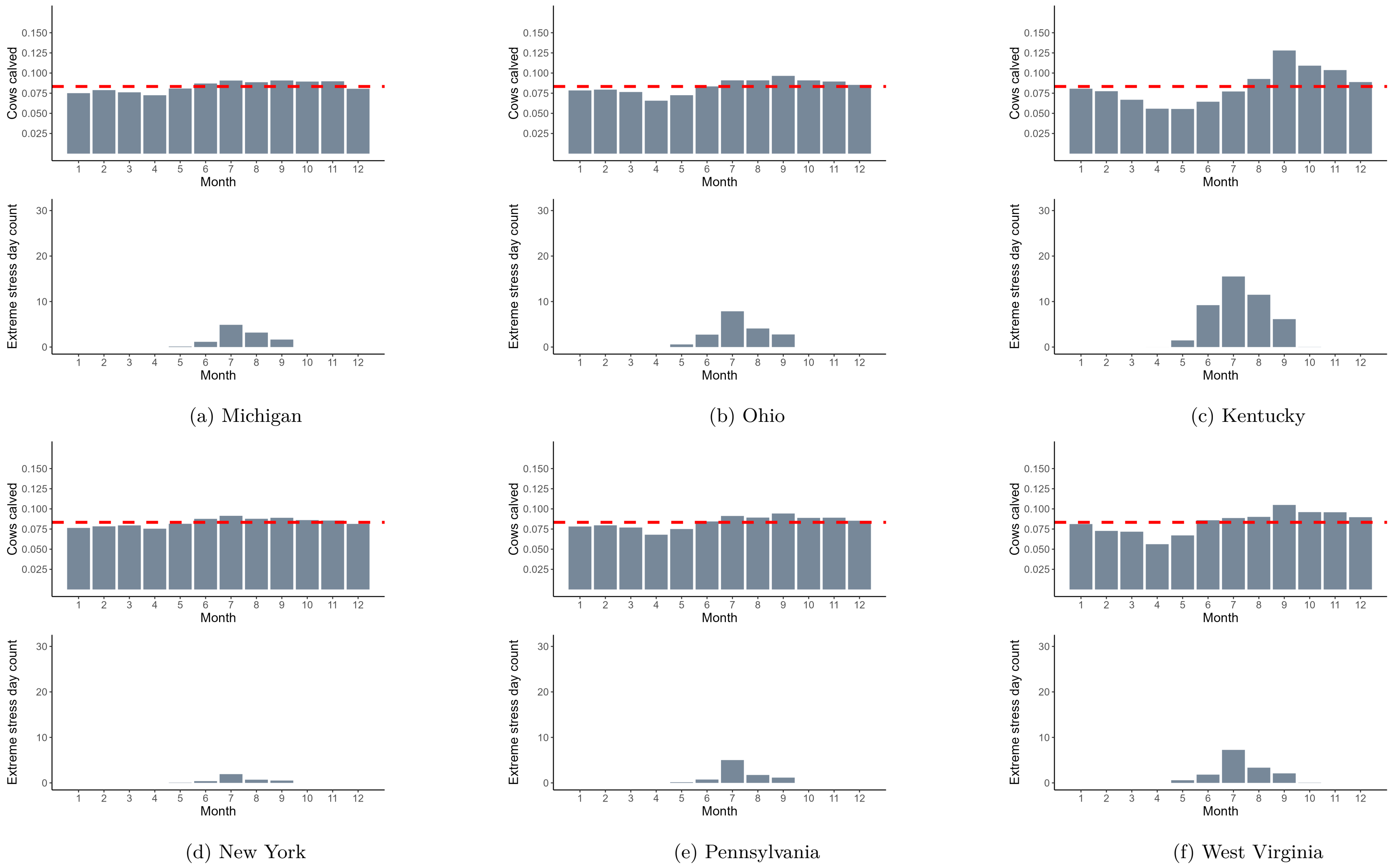
Seasonal calving patterns may also explain differences in average heat stress effect across states. For example, it may explain the high vulnerability of the herds in North Dakota to heat stress, as they have relatively more calves early in their production cycle in the summer. As such, the average losses across their herds are higher relative to a state that has fall calving patterns. Similarly, North Carolina experiences higher losses under extreme conditions than comparable states with more seasonal calving. However, these patterns do not explain the entire variation in heat stress effects, nor does the average number of heat stress events predict county-level calving patterns. Further research should investigate the conditions under which a farm adopts seasonal calving as well as the other management practices that farmers adopt to mitigate heat stress.



(a) Iowa (b) Indiana (c) Illinois

(d) Minnesota (e) North Dakota (f) South Dakota

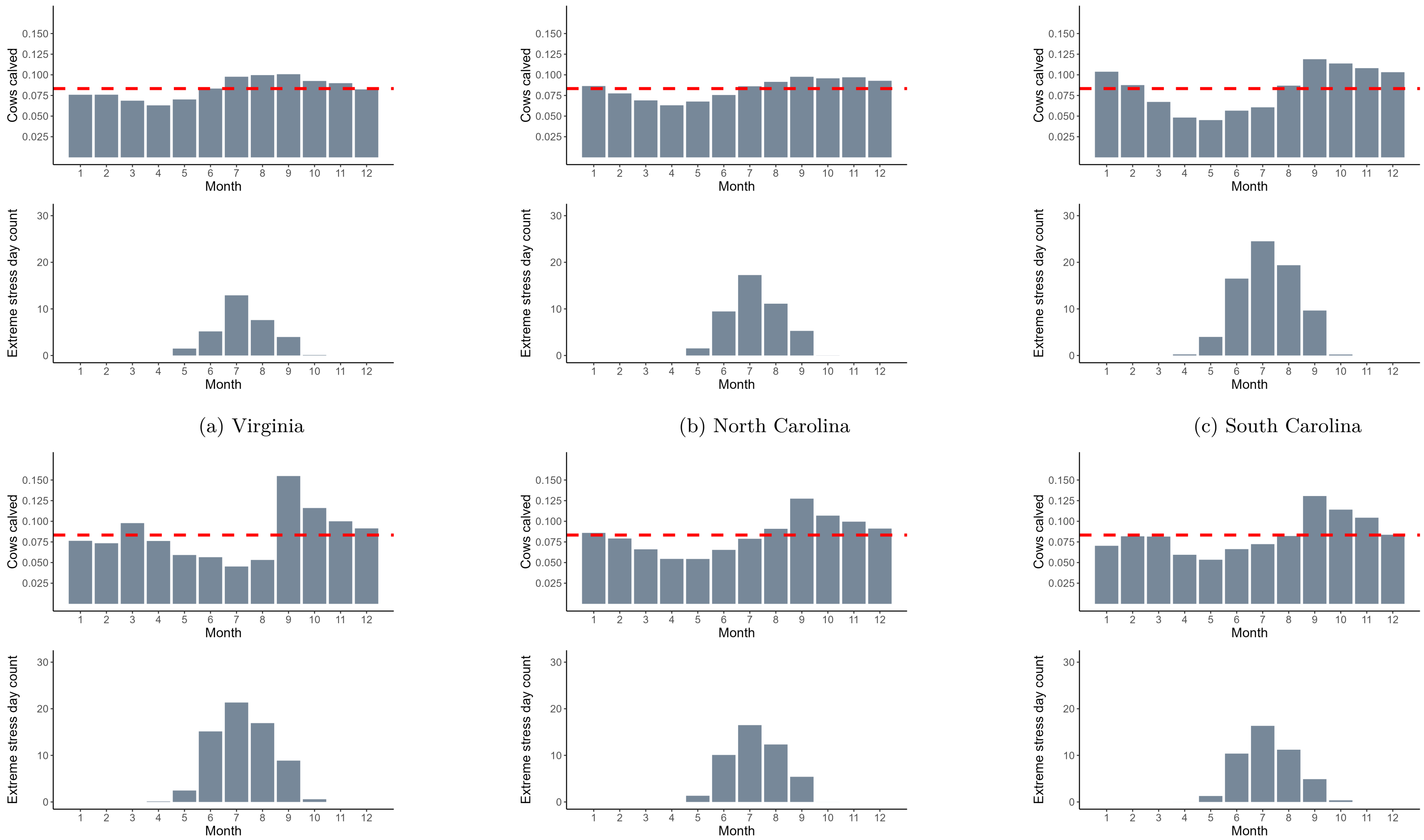
Figure 10: Calving Patterns and Average Heat Events in Select States



(a) Michigan (b) Ohio (c) Kentucky

(d) New York (e) Pennsylvania (f) West Virginia

Figure 11: Calving Patterns and Average Heat Events in Select States, Continued



(a) Virginia (b) North Carolina (c) South Carolina

(d) Arkansas (e) Tennessee (f) Missouri

Figure 12: Calving Patterns and Average Heat Events in Select States, Continued

4.3 Cost Calculations

We use the total weekly loss following a stress day using the average loss estimates from table 1 to calculate the total cost of heat stress for a hundred-cow herd in our sample. The average county in our sample experienced 390 low-stress, 206 medium-stress, and 125 extreme-stress days over the five-year period (78, 41, and 25 days per year, respectively). For a hundred-cow herd with an average yield of 80 pounds of energy-adjusted milk per cow, this is equivalent to 28,916 pounds of milk lost due to low-stress days, 42,953 pounds lost due to medium-stress days, and 72,073 pounds lost due to extreme stress. In total, a hundred-cow herd under the average weather conditions in our sample lost 143,942 pounds of energy-adjusted milk to heat stress over five years. At $10 profit per pound of milk, this is equivalent to $1.4 million dollars in lost profit over five years, or $287,888 per year.[5]

Next, we estimate a back of the envelope calculation of the total yield loss in our sample over the five-year period. In each county and each month, we estimate the total milking herd in the county and multiply this by the sample average winter yield of 81.8 pounds of milk per cow per day. This calculates a rough total county-level counterfactual yield. We multiply this yield by the total number of heat stress days in the county and the total yield lost due to that category of heat stress. We then multiply this loss, in pounds of milk, by the profit margin of milk in that month. Across all of the herds in our sample, we estimate a total loss of 975 million pounds of energy-adjusted milk over the period. This is composed of 263 million lost due to low-stress days, 336 million lost due to medium-stress days, and 376 million lost due to extreme-stress days. At actual profit margins per pound of milk, this is equivalent to $60 million in lost profit over 5 years. While losses varied greatly year-to-year, this comes out to $12 million in lost profit per year, on average.

Under current climate conditions, most of the losses are due to low- and medium-stress days. This is due to their combination of relatively high yield loss per cow and the frequency of these events. However, it is important to note that the yield loss per cow due to an extreme-stress day is nearly triple that of a medium-stress day. Under climate scenarios with more frequent extreme stress days, the costs could be far higher.

How much of these losses are due to vulnerable cattle? We calculate the total seven-day losses following one day of low, medium, or extreme stress for a multiparous cow early and late in their lactation cycle. The week following a day with positive heat load less than 35, multiparous cows lose 3.7% of a day's yield early in their cycle and have no losses late in their cycle. Similarly, multiparous cows lose 4.1% the week following a day with heat load from 35 - 70 that falls early in their cycle but experience no losses late in their cycle. Following a medium-stress day (70 - 140 heat load), they lose 5.6% early in

[5]In the period 2012 to 2016, the income over feed cost, a measure of the profit margin for dairy farms, was about $8.5 per pound of milk.

their cycle compared to 2.1% late in their cycle. Following an extreme-stress day, they lose 11.1% early in their cycle, compared to 7.6% late in their cycle. We use these numbers to estimate the total losses of multiparous cows early in their cycle in May through August and find these losses account for $31.4 million of the $60 million lost profit (52% of losses) in our sample.

Finally, how much loss could be averted if producers changed their calving dates? We estimate a back-of-the-envelope estimate of the avoided losses if all of the multiparous cows in our sample had been more than 120 day post-birth during the summer months (May - August). This is equivalent to a regional herd with no calving from February to August. We find this adjustment would have mitigated $22.69 million in lost profit.

This estimate does not include potential general-equilibrium effects of all herds shifting to a fall calving cycle. However, since the herds in our sample primarily supply milk for processed dairy products with a longer shelf life, we expect the general equilibrium effects to be minimal. Farms would additionally pay a one-time fixed cost of $2.50 per cow per day in lost production for the days that a cow was left dry as the farmer adjusted her calving schedule. It also does not include potential cost savings from failed insemination attempts, which are more likely under warmer conditions. If higher rates of insemination failure explain the current seasonality in calving, then avoiding attempts until temperatures are cooler could increase a herd's success rate provide an additional form of cost savings.

5 Conclusion

Our analysis calculates the impacts of heat stress on the US dairy sector using animal-level data from the Midwest in the period 2012-2016. After conducting a back of the envelope calculation, we calculate that $6.79 billion in dairy industry profits were lost in our five year period because of heat stress. Most of the losses in our sample are being driven by low- and medium- heat stress days with a heat load below 140. However, losses due to a single extreme heat event are at least double those of a single medium heat event. A scenario with more extreme stress days could see rapidly rising losses due to to heat stress. Similarly, we find that multi-day heat events, defined as three consecutive days of at least low stress, yield losses equivalent to a single day of extreme heat stress. Thus, our results demonstrate the potential for greater losses in a scenario with heat waves rather than single-day heat events. Finally, losses are greatest for cattle that are early in their production cycle and have given birth multiple times, who are also the major producers in a herd.

Our unique data allows us to understand how heat stress impacts different cohorts of dairy cattle across production cycles. Of the $6.79 billion in total losses, a little more than half of this loss was from cattle who were exposed to heat stress during their most vulnerable and most productive months. We estimate that about one-third of this loss would be averted by dairy farmers simply changing their calving dates so that these vulnerable dairy cattle are less exposed to heat.

In terms of evidence of adaptation, we see very little impacts of the lowest-stress days with a positive heat load under 35, despite the fact that cattle should see decreased milk production under these conditions. We do not find as large of impacts as previous studies, which suggests that some mitigation has likely taken place. With respect to calving dates, we see evidence that states with a large number of stress days have shifted calving dates to the fall instead of the spring. Some states with more spring calvings are also seeing larger heat stress impacts.

Our work demonstrates the vulnerability of livestock production, and dairy production in particular, to climate change. Despite being among the most technologically advanced in the world, US dairy producers experience significant losses from heat events. This raises concerns for low-income contexts where livestock production is a main income source and dairy products are a vital source of protein and calories. Yet, the potential for changes in calving dates to mitigate heat stress suggest there are still low-cost ways for livestock producers to buffer themselves from the harmful impacts of increasing heat.

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Appendix A THI heat load calculation

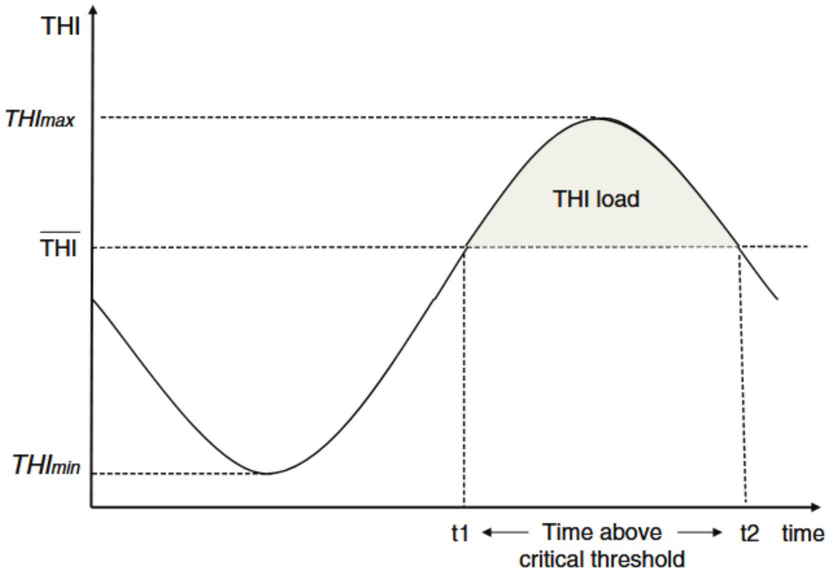
Our measure of heat exposure is THI heat load. Heat load measures the amount of time that cattle spend above their critical THI threshhold which we consider to be 72 (St-Pierre et al., 2003). Figure A1 is from Key et al. (2014) and shows that heat load is equivalent to the area under a sine curve fit using the THI min and max. Our heat load measure was calculated using the formula in the Appendix of St-Pierre et al. (2003) the THI min and max using this python script:

```
import numpy as np

P = 24

PI = np.pi


def heat_load(THI_min,THI_max,thresh):
    if thresh>=THI_max:
        res = 0
    else:
        THImean = (THI_max + THI_min)/2
        if thresh<THI_min:
            res = P*(THImean - thresh)
        else:
            amp = (THI_max-THI_min)/2
            if thresh>=THImean:
                x1 = np.arcsin((thresh-THImean)/amp)
                x2 = PI - x1
                res = (np.cos(x1)-np.cos(x2))*amp*P/2/PI - (x2-x1)*P/2/PI*(thresh-THImean)
            else:
                x1 = PI
                x2 = PI + np.arcsin((THImean-thresh)/amp)
                X = (np.cos(x2)-np.cos(x1))*amp*P/PI
                res = amp*P/PI + (THImean-thresh)*P/2 + (THImean-thresh)*((x2-PI)*P/PI) - X
    return res
```

Heat load is increasing in both THI max and THI min since they both increase the amount of exposure to heat. Figure A2 shows the relationship between THI max, THI min, and heat load. The common categories of low, moderate, and extreme stress days can roughly translate to different tiers of heat load. Low stress days with THI between 72 and 80 roughly translate to days where THI heat load is more than 0 and less than 70. Medium stress days with THI between 80 and 90 roughly translate to days where THI heat load is between 70 and 140. Finally, extreme stress days with THI above 90 usually have a heat load of at least 140.

Appendix B State-level coefficients

Figure A1: THI Load Model



Source: Key et. al. (2014)

Figure A2: THI max, min, and load

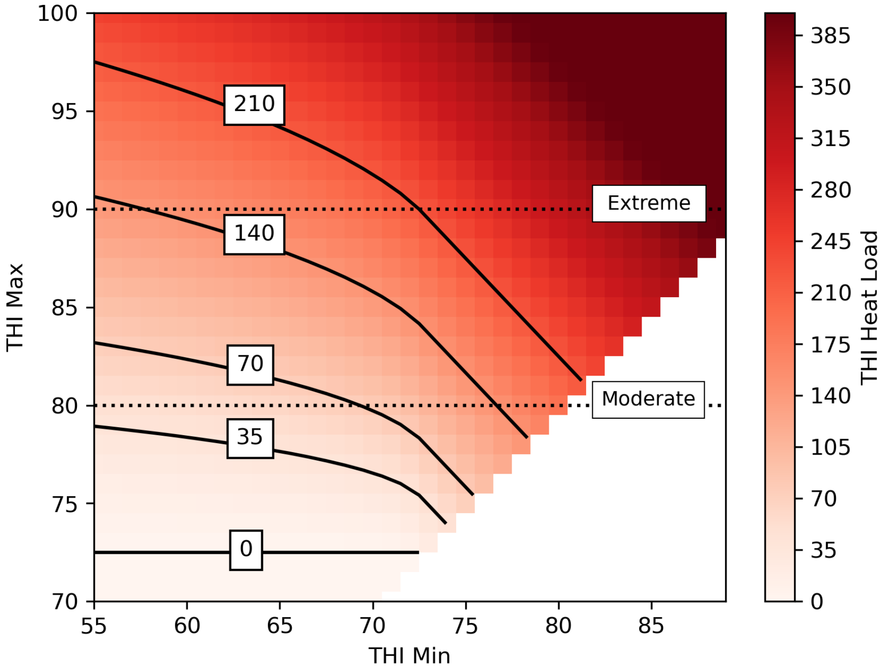


Table B1: State-level coefficients

State Name	Heat Load 0-35	35-70	70-140	140-210	> 210
Vulnerable					
South Carolina	-0.028	-0.040	-0.042	-0.051	-0.104
Arkansas	-0.016	-0.015	-0.044	-0.050	-0.043
North Dakota	-0.017	-0.023	-0.020	-0.047	-0.013
Illinois	-0.006	-0.012	-0.020	-0.027	-0.034
Missouri	-0.006	-0.011	-0.019	-0.021	-0.034
Low-Level Resilient					
North Carolina	0.001	-0.002	-0.008	-0.030	-0.035
Tennessee	-0.002	-0.018	-0.007	-0.022	-0.029
Iowa	-0.002	-0.005	-0.006	-0.020	-0.031
Kentucky	-0.001	-0.011	-0.009	-0.020	-0.033
Virginia	0.001	-0.002	-0.008	-0.018	-0.037
Michigan	-0.004	-0.006	-0.008	-0.012	-0.025
Minnesota	-0.000	-0.001	-0.007	-0.014	-0.021
South Dakota	-0.004	-0.009	-0.010	-0.004	-0.029
West Virginia	-0.002	-0.008	0.005	-0.025	-0.003
Nebraska	-0.001	-0.003	-0.007	-0.011	-0.011
Resilient					
New York	-0.002	-0.002	-0.005	-0.011	-0.004
Pennsylvania	-0.002	-0.008	-0.010	-0.009	-0.018
Indiana	-0.001	-0.006	-0.005	-0.008	-0.005
Ohio	-0.001	-0.001	-0.007	-0.010	0.001

Table B2: State-Level Heterogeneous Coefficients pt. 1

		Heat Load	North Carolina	North Dakota	Ohio	Pennsylvania	South Carolina	South Dakota	Tennessee	Virginia	West Virginia
Primi	< 120 DIM	0-35	-0.004	-0.023	-0.018	-0.009	-0.057	-0.046	-0.007	-0.005	0.001
		35-70	0.012	-0.044	-0.018	-0.011	-0.083	-0.042	-0.003	-0.003	-0.006
		70-140	0.005	-0.011	-0.022	-0.013	-0.064	-0.045	-0.003	-0.004	0.023
		140-210	0.005	-0.016	-0.016	-0.009	-0.051	-0.039	-0.005	-0.010	-0.004
		> 210	-0.012	-0.004	-0.011	-0.013	-0.084	-0.054	-0.003	-0.024	-0.020
	> 120 DIM	0-35	-0.002	-0.021	-0.004	-0.001	-0.000	-0.008	-0.001	0.000	-0.005
		35-70	-0.008	-0.024	-0.003	-0.007	-0.026	-0.018	-0.016	-0.004	-0.004
		70-140	0.000	-0.031	-0.010	-0.008	-0.037	-0.009	-0.010	-0.011	0.018
		140-210	-0.015	-0.063	-0.013	-0.008	-0.045	-0.018	-0.021	-0.018	-0.026
		> 210	-0.011	0.004	0.010	-0.016	-0.100	-0.029	-0.024	-0.043	0.042
Multi	< 120 DIM	0-35	-0.012	-0.039	-0.035	-0.029	-0.068	-0.041	0.013	-0.013	-0.013
		35-70	-0.016	-0.056	-0.041	-0.040	-0.061	-0.046	-0.009	-0.022	-0.040
		70-140	-0.043	-0.013	-0.048	-0.047	-0.060	-0.051	-0.000	-0.028	-0.036
		140-210	-0.067	-0.090	-0.057	-0.048	-0.082	-0.052	-0.018	-0.053	-0.058
		> 210	-0.081	-0.063	-0.075	-0.064	-0.133	-0.086	-0.043	-0.067	-0.072
	> 120 DIM	0-35	0.012	-0.003	0.011	0.009	-0.021	-0.000	0.002	0.011	0.004
		35-70	0.004	0.006	0.013	0.005	-0.031	-0.007	-0.018	0.009	0.006
		70-140	-0.002	-0.029	0.009	0.005	-0.035	-0.012	0.000	0.002	0.011
		140-210	-0.034	-0.035	0.004	0.005	-0.047	0.011	-0.019	-0.003	-0.018
		> 210	-0.037	-0.004	0.026	-0.002	-0.105	-0.024	-0.024	-0.024	0.004

Table B3: State-Level Heterogeneous Coefficients pt. 2

		Heat Load	Arkansas	Illinois	Indiana	Iowa	Kentucky	Michigan	Minnesota	Missouri	Nebraska	New York
Primi	< 120 DIM	0-35	0.003	-0.016	-0.014	-0.011	0.007	-0.017	-0.022	-0.010	-0.008	-0.017
		35-70	-0.033	-0.037	-0.009	-0.020	0.012	-0.008	-0.021	-0.013	-0.013	-0.017
		70-140	-0.005	-0.024	-0.017	-0.018	0.010	-0.013	-0.020	-0.006	-0.012	-0.021
		140-210	-0.025	-0.031	-0.009	-0.025	-0.002	-0.010	-0.022	-0.011	-0.018	-0.021
		> 210	-0.016	-0.024	0.005	-0.034	-0.018	-0.019	-0.025	-0.017	0.000	-0.024
	> 120 DIM	0-35	-0.025	-0.003	-0.007	-0.003	0.006	-0.010	0.001	-0.007	-0.000	-0.006
		35-70	0.007	-0.016	-0.010	-0.003	-0.002	-0.006	0.001	-0.007	-0.018	-0.006
		70-140	-0.064	-0.022	-0.006	-0.006	-0.007	-0.017	-0.006	-0.017	-0.007	-0.009
		140-210	-0.028	-0.026	-0.018	-0.021	-0.014	-0.021	-0.009	-0.016	-0.019	-0.012
		> 210	-0.031	-0.036	-0.009	-0.034	-0.036	-0.028	-0.016	-0.030	-0.016	0.000
Multi	< 120 DIM	0-35	-0.011	-0.038	-0.019	-0.028	0.018	-0.038	-0.038	-0.003	-0.023	-0.040
		35-70	-0.016	-0.042	-0.023	-0.034	-0.010	-0.043	-0.040	-0.021	-0.024	-0.042
		70-140	-0.029	-0.055	-0.035	-0.039	-0.005	-0.049	-0.051	-0.032	-0.038	-0.045
		140-210	-0.070	-0.072	-0.035	-0.057	-0.028	-0.060	-0.062	-0.036	-0.037	-0.053
		> 210	0.005	-0.072	-0.039	-0.079	-0.029	-0.067	-0.070	-0.053	-0.041	-0.011
	> 120 DIM	0-35	-0.001	0.006	0.018	0.007	0.002	0.012	0.012	0.004	0.010	0.010
		35-70	-0.005	0.008	0.005	0.004	-0.006	0.002	0.011	0.000	0.020	0.010
		70-140	-0.034	-0.007	0.014	0.006	0.002	0.009	0.006	-0.009	0.009	0.007
		140-210	-0.045	-0.010	0.012	-0.008	-0.009	0.009	-0.002	-0.012	0.009	-0.002
		> 210	-0.054	-0.024	0.012	-0.011	-0.019	-0.016	-0.009	-0.025	0.003	-0.013