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# Heat risks in Swiss milk production

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**Abstract**

Heat stress can affect milk production in several ways. We here quantify overall farm-level heat effects on annual milk revenues, veterinary expenses, and feed purchases in Swiss agriculture. We combine farm-level accountancy panel data from 1314 representative Swiss milk producers and covering 13 years with high-quality weather data in a reduced-form two-way fixed effect model. Although we find that Swiss milk producers frequently encounter heat stress, we find no significant heat effects on annual milk revenues, veterinary expenses, or feed purchases. This finding implies that Swiss milk farms are on average robust to current heat exposure.

**KEYWORDS**

heat effects, milk revenues, piecewise linear splines, production costs

**JEL CLASSIFICATION**

Q12, Q14, Q54

## 1 | INTRODUCTION

Extreme weather and climate change pose a serious threat to the agricultural sector and put farmers in many parts of the world at risk (Hsiang, 2016; Lobell et al., 2011; Moore et al., 2017; Ortiz-Bobea et al., 2021). This is particularly the case for the dairy sector, which is a major contributor to global food production and food security (FAO, 2020; OECD & FAO, 2018). Especially heat exposure is among the most important risks in dairy production. Heat can affect not only milk quantity and quality but possibly also production costs by affecting, for example, feed production and animal health (Key & Sneeringer, 2014; Nardone et al., 2010; Ortiz-Bobea et al., 2018; Perez-Mendez et al., 2019; Schlenker & Roberts, 2009; St-Pierre et al., 2003; Tubiello et al., 2007).

In this paper, we empirically assess overall effects of heat exposure on annually observed milk revenues, veterinary expenses, and feed purchases at the farm level in Swiss milk production. To this end, we combine farm-level accountancy panel data with high-quality weather data in an econometric model that reflects overall and potentially nonlinear heat effects and that implicitly accounts for endogenous adaptation measures in response to heat exposure.

There is a wide range of studies assessing empirical heat effects on milk quantity or milk revenues. Many of these studies have used a temperature-humidity-index (THI) to assess the effects of heat stress on dairy production. For instance, Mayer et al. (1999) find a direct negative effect of heat stress on milk production in Australia, Ogundeji et al. (2021) in South Africa, Ageeb and Hayes (2000) in Sudan, Hammami et al. (2013) in Luxembourg, Finger et al. (2018) in Germany and Key and Sneeringer (2014), Mukherjee et al. (2013), Qi et al. (2015) and St-Pierre et al. (2003) in the United States. Moreover, Perez-Mendez et al. (2019) find no direct effect of heat stress on milk cows in the Spanish region of Asturias, but they find that weather may indirectly affect milk production through reduced feed production. Especially heat exposure can reduce pasture and crop production as well as feed quality (Lobell et al., 2011; Ortiz-Bobea et al., 2018; Schlenker & Roberts, 2009; Tubiello et al., 2007). Moreover, literature shows potentially negative effects of heat exposure on animal health (Kadzere et al., 2002; Nardone et al., 2010). In summary, literature has identified different ways in which heat exposure can affect milk production and shown that the mechanisms at work and their effects can vary substantially between case studies. However, no study has empirically estimated heat effects on milk revenues and production costs simultaneously.

This paper aims to estimate possible heat effects on empirically observed annual milk revenues and simultaneously also on empirically observed veterinary expenses and feed purchases at the farm level. Thus, this paper does not only consider possible heat effects on revenues but also on selected production costs for which the literature indicates possible heat effects.[1] Observed annual milk revenues, veterinary expenses, and feed purchases implicitly take into account quality-dependent prices for the milk produced, veterinary services, and purchased feed, and are of highest economic interest to farmers because they affect farmers' incomes. Our estimations of overall heat effects on these economic variables provide decisive information to improve specific risk management components. To this end, we provide an analysis of Swiss milk production, which contributes approximately 20% to the total agricultural output in Switzerland (Federal Statistical Office, 2020). The identification of heat effects in different milk production systems is important because resilience, that is, the system's ability to ensure the provision of its functions, varies across production systems and may require different risk management tools and policy recommendations (Meuwissen et al., 2019). In this context, the Swiss milk production system is of lower intensity, has lower heat exposure, and different structural, economic, political, and environmental conditions than previously analyzed milk production systems such as in Australia (e.g., Mayer et al., 1999), Germany (e.g., Finger et al., 2018), or the United States (e.g., Gisbert-Queral et al., 2021).

We leverage an unbalanced panel data set consisting of 9894 observations for each accountancy variable spanning over 13 years within a farm and year-fixed effects model, that is, we estimate these heat effects via the within-farm and within-year variation of the accountancy variables and year-to-year changes in exogenous, farm-specific weather exposure while controlling for a myriad of time-invariant and year-specific confounders. The model also considers management adaptation, that is, implicitly accounts for potential interactions between heat exposure and management and thereby captures overall (i.e., the sum of direct and indirect) heat effects on milk revenues, veterinary expenses and feed purchases. Moreover, the model can reflect potentially nonlinear heat exposure with a piecewise linear function and identify critical heat thresholds itself.

We find that Swiss milk producers frequently encounter potentially harmful heat exposure, but this exposure has no significant effects on annual milk revenues, veterinary expenses, or feed purchases.

[1] Heat exposure may also affect other production costs than veterinary expenses or feed purchases, such as energy or insemination expenses. We focus on veterinary expenses and feed purchases because these variables are clearly allocable to milk production in our data set. The majority of Swiss farms have a diversified production portfolio and many accountancy variables in the data set, such as energy expenses, summarize costs from different activities so that we cannot compute profits from milk production or estimate heat effects on other potentially heat-sensitive milk production costs.

The remainder of the paper is structured as follows. Supporting Information: Section A1 provides an overview of heat stress mechanisms in dairy production. Building on this, Section 2 introduces our estimation and identification strategy. Section 3 presents the case study and data. Next, we show the results in Section 4 that is followed by a discussion in Section 5. Finally, we end the paper with concluding remarks.

## 2 | EMPIRICAL FRAMEWORK

This section introduces our methodological framework. Section 2.1 “Estimation strategy” presents the empirical model and the thermal indices applied in this study. Section 2.2 “Identification strategy” explains why this model supports the identification of overall heat effects and how we address heterogeneity in our sample and measurement errors in weather data.

### 2.1 | Estimation strategy

The aim of this paper is to empirically estimate heat effects on annually observed milk revenues, veterinary expenses, and feed purchases at the farm level. Supporting Information: Section A1 shows the various mechanisms in which heat stress can affect these three variables and that these mechanisms are often interrelated. Therefore, we do not aim to identify exact mechanisms, but we aim to estimate overall (direct and indirect) heat effects by using a reduced-form regression model to link exogenous thermal measurements to each of the three accountancy variables, that is, we use a model that does not make assumptions on the various and interrelated mechanisms of heat stress on the dependent accountancy variables. More specifically, we estimate the two-way (farm and year) fixed effects model shown in Equation (1) for each accountancy variable.

$$\log(y_{it}) = \int_{\underline{h}}^{\bar{h}} g(h) \times \Phi_{it}(h)\,dh + \delta_1 p + \delta_2 p^2 + \alpha_i + \gamma_t + \varepsilon_{it}. \tag{1}$$

The dependent variable $\log(y_{it})$ is the logarithm of either annual milk revenues, veterinary expenses, or feed purchases at farm $i$ and in year $t$. The function $g(h)$ estimates the effects of exogenous thermal measurements $h$ on the dependent variable $\log(y_{it})$ and $\Phi_{it}(h)$ is the time distribution of thermal measurements over a specific measurement period. We define this measurement period from the beginning of April to the end of October because this is the growing season for feed production in Switzerland and there is no heat exposure in the cold winter season from November to March for cows and feed plants.[2] The lower thermal bound $\underline{h}$ and the upper thermal bound $\bar{h}$ mark the thermal range, that is, the measurements of the thermal variable measured from the beginning of April to the end of October. We use exogenously cumulative precipitation over the measurement period and its square $(\delta_1 p + \delta_2 p^2)$ as control variables because precipitation amounts are likely to be correlated with heat exposure and to affect annual milk revenues, veterinary expenses, or feed purchases in different ways than temperature or humidity (Auffhammer et al., 2013; Blanc & Schlenker, 2017; Perez-Mendez et al., 2019). The farm-fixed effects $\alpha_i$ control for unobserved time-invariant but farm-specific confounders such as production systems. The year-fixed effects $\gamma_t$ control for unobserved farm-invariant but year-specific confounders such as price-levels and (often abrupt) policy changes.[3] Hence, we estimate heat effects via the within-farm and within-year variation of the three accountancy variables, respectively,

[2] The average daily maximum temperature between November to March is 5.56°C in our sample, that is, there is no heat stress during this period.

[3] Switzerland has adjusted its agricultural policy several times over the past decades and these adjustments have also influenced milk production and milk prices (Finger et al., 2017; Renner et al., 2021).

and year-to-year changes in farm-specific weather exposure. Finally, the error term $\varepsilon_{it}$ summarizes any other confounders that influence the dependent variable. We cluster standard errors by farm and year because the error term $\varepsilon_{it}$ might be heteroscedastic and show spatial as well as temporal autocorrelation.

We need to approximate the integral shown in Equation (1) and specify the functional form of $g(h)$. We do so by following Schlenker and Roberts (2009) and use a piecewise linear spline function. After dividing the independent variable (i.e., the thermal variable) into intervals, this specification estimates a linear relationship between the dependent (i.e., the accountancy variables) and independent variable for each interval and connects the resulting piecewise linear relationships. This method has two advantages. First, it can account for nonlinear heat effects because the overall response of the dependent variable is composed of connected piecewise linear responses. Second, the estimated models show the critical heat values from which revenues or costs start to decline or increase, that is, we do not have to make a priori assumptions about critical thermal values as often done in similar studies (e.g., Finger et al., 2018; Mukherjee et al., 2013; Perez-Mendez et al., 2019; Qi et al., 2015; St-Pierre et al., 2003). This is important because critical thermal values depend on the cow breed or feed species, environment, management, and interactions of these variables. Especially endogenous adaptation measures taken by farmers in response to heat exposure (e.g., activation of ventilation systems, adjusting nutritional management, reducing herd size, etc.) may reduce or eliminate heat stress at levels that were originally identified as critical (Bohmanova et al., 2007; Gisbert-Queral et al., 2021; Kadzere et al., 2002; Mayer et al., 1999). Moreover, research used experimental settings in climate chambers to estimate critical heat-values for cow breeds different from cows in Switzerland. Thus, these critical heat-values might not be representative for pasture-based Swiss milk production (see e.g., Mayer et al., 1999 who find considerably different critical heat-values for free roaming animals in Australia than earlier identified in climate chambers in the United States). The arguments for not using pre-defined critical thresholds to estimate temperature effects on feed production are similar (Schlenker & Roberts, 2009).

We follow previous literature (e.g., Bucheli et al., 2022; Schlenker & Roberts, 2009) and set the knots, that is, the breaking points that divide the independent variable (i.e., the thermal variable) into intervals, so that the estimated Equation (1) has the largest goodness of fit. See Supporting Information: Section A2.1 for details on how to derive the model with largest goodness of fit. Using this procedure allows us to include the wide spread of critical THI and temperature thresholds that have been identified or used in earlier literature.[4] Thus, we do not have to define critical thresholds a priori and choose critical threshold using a goodness of fit criterion.

In addition to the approximation of the integral, Equation (1) requires the specification of a thermal measurement $h$. We use a THI to regress heat effects on annual milk revenues and veterinary expenses because cows' responses to heat stress depend on the combination of temperature and relative humidity as highlighted in Supporting Information: Section A1. More specifically, we use the THI-formula shown in Equation (2) because this THI is suitable for pasture-based milk production and the Swiss climate (Bohmanova et al., 2007; Finger et al., 2018; Hammami et al., 2013; Herbut et al., 2018; Lambertz et al., 2014).[5]

$$\mathrm{THI} = (1.8 \times T_{\mathrm{db}} + 32) - (0.55 - 0.0055 \times \mathrm{RH}) \times (1.8 \times T_{\mathrm{db}} - 26). \tag{2}$$

$T_{\mathrm{db}}$ denotes the dry bulb air temperature in degrees Celsius and RH is the relative air humidity in percentage to saturation.

[4]These critical THI-values can range from 65 (Ogundeji et al., 2021) to 87 (Mayer et al., 1999) and depend on factors such as cow breed, production system, and management. The literature does not indicate a critical threshold for Swiss milk production, but our estimation strategy considers the range of critical thresholds used in earlier studies. See also Section 2.2 (Identification strategy).

[5]The THI was calibrated in climatic chambers to assess heat effects on milk production but not to assess the effects of cold stress on milk production. Thus, we only consider THI-values during the growing season and exclude cold months (November–March) that do not bring any additional heat exposure in Switzerland. This is in line with previous studies (e.g., Finger et al., 2018; Key & Sneeringer, 2014; St-Pierre et al., 2003).

We use air temperature in degree-celsius (°C) to regress heat effects on feed purchases because air temperature can have a negative impact on feed production (e.g., Ortiz-Bobea et al., 2018; Schlenker & Roberts, 2009).

Both the THI and temperature can show considerable fluctuations within a day, but weather data is often only available at a daily resolution and does therefore not capture these fluctuations to the full. We follow previous research and approximate within-day THI-values (e.g., Finger et al., 2018; St-Pierre et al., 2003; Vroege, 2020) and within-day temperatures (e.g., Bucheli et al., 2022; D'Agostino & Schlenker, 2016; Gammans et al., 2017; Ortiz-Bobea et al., 2018; Snyder, 1985; Tack et al., 2015) by using daily weather variables to fit daily sine curves.[6] Subsequently, we derive hourly THI-values and temperatures from the fitted daily sine curves. See Supporting Information: Section A2.2 for further details.

## 2.2 | Identification strategy

There are several reasons why the use of a reduced-form panel model with farm and year-fixed effects is particularly suitable to identify these overall heat effects (see also Auffhammer, 2018; Auffhammer et al., 2013; Blanc & Schlenker, 2017; Hsiang, 2016).

First, a reduced-form model, that is, a model with only exogenous independent variables, captures heat effects through all possible ways and therefore captures the overall heat effects on the dependent variable.[7] Second, a reduced-form model implicitly accounts for endogenous management adaptations in response to heat exposure meaning that the model accounts for endogenous management adjustments that mitigate heat risks. For instance, farmers can adjust the nutritional management (e.g., grazing during cool nights, provision of cool water), activate ventilation systems, irrigate pastures and feed crops or adjust the herd composition (e.g., selling older and less productive animals). The consideration of these endogenous management practices in response to heat stress is important because they can substantially reduce or even eliminate the impact of heat exposure on our three accountancy variables (Auffhammer, 2018; Bohmanova et al., 2007; Kadzere et al., 2002; Mayer et al., 1999).

Third, the fixed effects control for a myriad of possible confounders. The farm fixed effects absorb unobserved time-invariant confounders such as the production system or soil characteristics. The year-fixed effects capture unobserved confounders such as improvements in animal or feed genetics as well as (often abrupt) changes in agricultural policy and markets. Thus, these fixed effects reduce the omitted variable bias of our estimates. Fourth, the fixed effects transform the weather variables into *exogenous* weather shocks, that is, the transformation is a demeaning procedure so that weather shocks are interpreted as *exogenous* deviations from their farm-specific means. Finally, panel models offer more degrees of freedom than cross-sectional models. This is relevant for this paper because our thermal variables are likely to be correlated with precipitation that we use as control variable (Auffhammer et al., 2013).

We face the challenge of potentially heterogeneous heat effects due to heterogeneous structural, environmental, socioeconomic and political conditions in Swiss milk production (Renner et al., 2021). Thus, we include farms from all over Switzerland from the official farm accountancy data set (called complete sample hereafter) to identify an overall average effect, but also split this

[6] It has been shown that this intraday approximation is superior to the use of daily average values or higher levels of aggregation (e.g., Gammans et al., 2017; St-Pierre et al., 2003; Tack et al., 2015).

[7] A structural model (e.g., a production function that considers managerial factors) can identify determinants of variability in the dependent variable and show mechanisms in which heat affects milk production (see e.g., Perez-Mendez et al., 2019). A structural model may also result in a model with larger goodness of fit than a reduced-form model. However, these models are more prone to biased estimates because endogenous, heat-dependent variables are likely to absorb some heat effects (see also Hsiang, 2016). Consequently, a reduced-form model fits better to our research question.

sample and conduct the estimations shown in Equation (1) separately for farms in the plain, hill or mountain region (called plain sample, hill sample and mountain sample hereafter).

Another challenge is weather data quality, that is, measurement errors in the weather data that can bias our estimates[8] (Auffhammer et al., 2013; Blanc & Schlenker, 2017; Hausman, 2001). We address the challenge of interpolation errors, a main source of measurement error in weather data, by using high-quality gridded temperature and precipitation data provided by meteorologists and climatologists from the Federal Office of Meteorology and Climatology MeteoSwiss (e.g., Frei, 2014; Isotta et al., 2019). These gridded datasets contain interpolated weather data based on a dense and homogenized weather station network and on the latest interpolation techniques that particularly account for Swiss topography and climates and thus minimize the measurement error compared to weather station data. For relative humidity, we use data from the farm's closest weather station using three-dimensional Euclidean distances because a gridded data set for relative humidity is currently not available. We reduce measurement errors in relative humidity by exploiting a relatively dense and homogenized weather station network provided by the meteorologists of MeteoSwiss that is able to capture the variability in relative humidity in Switzerland, by penalizing differences in elevation between weather stations and farms and excluding stations with frequent technical failures. See Supporting Information: Section A3.3 for details.

Finally, we might face the challenge of low statistical power that may cause a type II error if effects are very small. We address this challenge by exploiting a comparatively large sample and calculating minimum detectable slopes of regression coefficients.

## 3 | CASE STUDY AND DATA

Milk production is among the most important agricultural activities in Switzerland. The value of dairy products produced annually in Switzerland is equivalent to approximately 2.1 billion Swiss francs, which is approximately 20% of the annual agricultural output (Federal Statistical Office, 2020). Milk production is mostly pasture-based and grasslands, which cover about 70% of agricultural land, form the backbone of feed production and shape Swiss landscapes in all regions. Although the government has progressively reduced protective measures in its agricultural policy, including the abolition of milk quotas in 2009, the dairy sector remains highly protected (Finger et al., 2017; Hillen, 2021; Hillen & von Cramon-Taubadel, 2019). As a result, the milk price received by Swiss producers is approximately double than in neighboring countries. The pricing mechanism depends to a certain degree on domestic demand and supply, region, quality, and purpose of use (industrial dairy milk or cheese), production type (conventional or organic), and farmers' potential memberships in producer associations with marketing programs (e.g., fair milk). Historical milk prices show low variability and have decreased from 2003 to 2015 as shown in Supporting Information: Figure A7 in Section A3.2. Dairy farms usually have a diversified production portfolio, including other animal and plant production. Compared to other milk-producing countries in Europe (e.g., Germany [Finger et al., 2018; Lambertz et al., 2014], Belgium [Vroege, 2020], and Luxembourg [Hammami et al., 2013]), the milk production is characterized by lower yields—the average milk production per cow and year in our sample is 6592 kg.

The climate is generally temperate, but climatic conditions can vary across Switzerland (Frei, 2014). Depending on environmental and socioeconomic factors, farms are classified into three distinct production regions: the plain region, hill region, and mountain region.

[8]We do not expect potential measurement errors in the accountancy data to bias our estimates because such errors, if there are any, are unlikely to correlate with weather exposure (Hausman, 2001; Ortiz-Bobea et al., 2021).

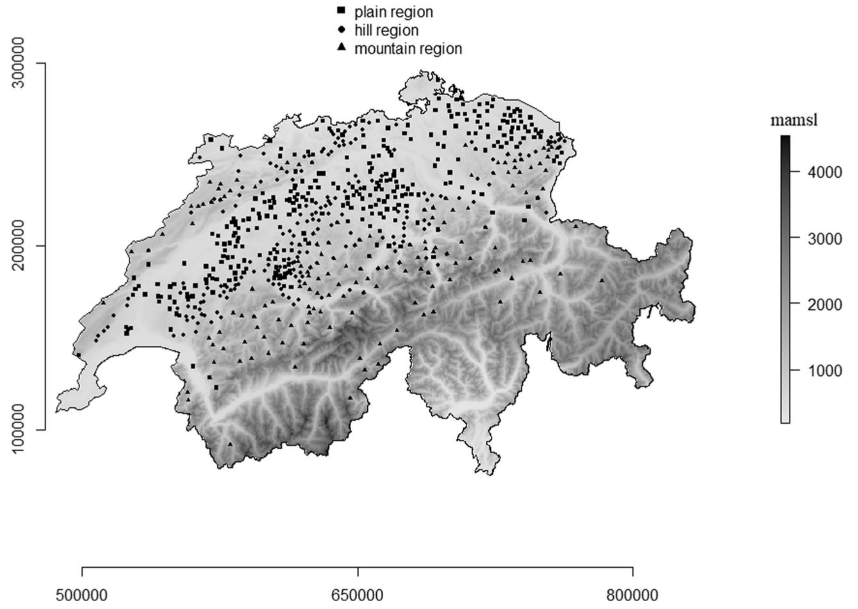


**FIGURE 1** Approximated farm locations in our case study in Switzerland. *mamsl* is meters above mean sea level. Swiss coordinate system LV03. Data source: Federal Office of Topography and Swiss Confederation's center of excellence for agricultural research (Agroscope).

## 3.1 | Farm accountancy data

The Swiss Confederation's center of excellence for agricultural research (Agroscope) provides farm-level accountancy data from milk producers from the official Swiss Farm Accountancy Data Network (FADN) (Hoop & Schmid, 2015). This data set consists of representative farms, aims to monitor the economic development of Swiss agriculture, and has been used in previous publications (e.g., de Mey et al., 2016; Renner et al., 2021; Schorr & Lips, 2018). Our subsample from the Swiss FADN consists of the 1314 milk producers shown in Figure 1. The records date from 2003 to 2015 (13 years),[9] resulting in 9894 observations for annual milk revenues, veterinary expenses, and feed purchases,[10] respectively. Each of these farms generates milk revenues, has been in the panel for at least 4 years, and keeps only milk cows as part of the animal production portfolio so that we can clearly allocate veterinary expenses and feed purchases to milk production. Table 1 shows descriptive statistics of accountancy data and weather data at farm level. Supporting Information: Section A3.1 provides additional information.

## 3.2 | Weather data

The Federal Office of Meteorology and Climatology (MeteoSwiss) provides daily minimum and maximum temperature as well as daily precipitation data in the form of homogenized gridded datasets. These gridded datasets have a spatial resolution of $1 \times 1$ km and are based on the latest interpolation techniques that particularly account for Swiss climates and topography

[9] Data collection changed after 2015 so that we restrict our analysis to the period from 2003 to 2015. The data set provides detailed accountancy records at farm level but does not contain information about farm characteristics (e.g., facilities, management).

[10] Feed purchases are the sum of concentrated feed and other feed (e.g., green fodder).

**TABLE 1** Descriptive statistics for farm-level accountancy and weather data, 2003–2015

| Variable | Sample | Mean | Median | IQR | Max | SD |
|---|---|---|---|---|---|---|
| Milk revenues (CHF) | Complete | 91,291 | 77,823 | 67,224 | 586,566 | 62,930 |
| | Plain | 119,989 | 105,175 | 68,999 | 586,566 | 68,687 |
| | Hill | 95,162 | 80,926 | 56,952 | 495,444 | 55,198 |
| | Mountain | 51,016 | 44,558 | 38,392 | 296,425 | 36,120 |
| Veterinary expenses (CHF) | Complete | 5037 | 4188 | 3902 | 38,561 | 3612 |
| | Plain | 6041 | 5203 | 4187 | 38,561 | 3976 |
| | Hill | 5220 | 4353 | 3798 | 31,081 | 3602 |
| | Mountain | 3567 | 2993 | 2682 | 31,081 | 2512 |
| Feed purchases (CHF) | Complete | 20,121 | 15,172 | 16,702 | 220,782 | 18,270 |
| | Plain | 22,641 | 16,605 | 18,945 | 220,782 | 21,491 |
| | Hill | 21,399 | 16,484 | 17,880 | 27,329 | 18,254 |
| | Mountain | 15,635 | 12,488 | 12,817 | 111,571 | 12,075 |
| Hourly THI (unitless) | Complete | 47.59 | 48.00 | 19.42 | 95.80 | 13.29 |
| | Plain | 49.83 | 50.24 | 19.41 | 95.52 | 12.94 |
| | Hill | 47.84 | 48.33 | 19.29 | 95.15 | 13.12 |
| | Mountain | 44.50 | 45.00 | 19.07 | 95.80 | 13.33 |
| Hourly temperature (°C) | Complete | 8.13 | 8.10 | 12.79 | 37.90 | 8.61 |
| | Plain | 9.56 | 9.53 | 13.00 | 37.90 | 8.55 |
| | Hill | 8.31 | 8.35 | 12.67 | 37.62 | 8.47 |
| | Mountain | 6.15 | 6.18 | 12.29 | 36.60 | 8.44 |
| Cumulative precipitation (mm) | Complete | 870 | 856 | 299 | 1660 | 214 |
| | Plain | 741 | 728 | 203 | 1508 | 161 |
| | Hill | 890 | 886 | 263 | 1598 | 194 |
| | Mountain | 1005 | 999 | 283 | 1660 | 199 |

*Note*: Weather data measured between the months of April to October. The complete sample consists of 1314 farms, the plain sample has 488 farms, hill sample has 438 farms, and the mountain sample has 386 farms. Yearly distributions of the accountancy variables are shown in Supporting Information: Figures A1–A3, and yearly distributions of weather data are shown in Supporting Information: Figures A9–A11.

Abbreviations: CHF, Swiss Francs; IQR, interquartile range; mm, millimeter; SD, standard deviation; THI, temperature-humidity-index; °C, degree celsius.

(Frei, 2014).[11] Additionally, MeteoSwiss provides data on daily minimum and maximum relative humidity from 53 weather stations. These weather stations are placed so that they provide representative weather data for Switzerland, that is, station density is larger in topographically heterogeneous regions such as mountainous regions. Supporting Information: Section A3.3 provides additional information.

[11] Detailed documentation on the gridded datasets can be found here: https://hyd.ifu.ethz.ch/research-data-models/meteoswiss.html (last accessed 27.10.2021). The use of quality-checked and homogenized datasets minimizes measurement errors in weather data and prevents biased estimates resulting from changing weather station densities (Auffhammer et al., 2013).

We use the statistical software environment R (R Core Team, 2018) for data handling, computations, and creation of illustrations. The packages "lspline" (Bojanowski, 2017) and "fixest" (Berge, 2018) are used to estimate Equation (1). All codes are available online: https://github.com/AECP-ETHZ/Heat-Risks-in-Swiss-Milk-Production.

## 4 | RESULTS

We do not find significant effects of heat exposure on annually observed milk revenues, veterinary expenses, and feed purchases at the farm level for milk producers in Switzerland. Figure 2 (Figure 3) shows the estimated average hourly THI effects on annual milk revenues (veterinary expenses). Similarly, Figure 4 illustrates the estimated average hourly temperature effects on feed purchases.[12] Each of these three figures has four subpanels that represent either the complete sample (top left), the sample with farms in the plain region (top right), farms in the hill region (bottom left), and farms in the mountain region (bottom right). The $y$-axis in each subpanel displays the logarithmic response of annual milk revenues (Figure 2), veterinary expenses (Figure 3), or feed purchases (Figure 4) to an hourly exposure of the thermal unit shown on the $x$-axis (THI in Figures 2 and 3 and air temperature in Figure 4). Within each subpanel, the inner line in red shows the estimated average effect of an hourly exposure to the unit displayed on the $x$-axis. The two outer lines mark the 95% confidence bands that we correct for potentially spatial and temporal dependence. We center the effects so that the sample's average hourly THI (in Figures 2 and 3) or the sample's hourly air temperature (in Figure 4) has no effect on the dependent variable on the $y$-axis in each subpanel, that is, all effects are relative to the effect of the sample's average hourly THI-value (Figures 2 and 3) or sample's average hourly temperature (Figure 4). Figures 2–4 only display exposure to observed moderate and extreme THI and temperature values because this is the focus of this paper and the purpose of the THI is to capture heat stress. However, all hourly THI-values and temperatures are considered in our model shown in Equation (1). Note that thresholds for potentially harmful THI-values (approximately around 72) and temperatures (approximately 30°C) are frequently observed (see Supporting Information: Section A3.3).

For Figure 2 (Figure 3), we can interpret the numbers on the $y$-axis as deviations (in percentage) from farm-specific means of annual milk revenues (veterinary expenses) if we substitute an hour at the sample's average hourly THI-value with another hourly THI-value from the $x$-axis. Similarly, the numbers on the $y$-axis in Figure 4 show deviations (in percentage) from farm-specific means of feed purchases if we substitute an hour at the sample's average hourly temperature with another hourly temperature value from the $x$-axis. The effect of an hourly exposure to a specific THI-value or temperature is statistically significant if both confidence bands are above or below the horizontal 0 line (on the $y$-axis). For instance, the average hourly THI-value of the complete sample is 47.59 (see Table 1). If we substitute an hour at a THI-value of 47.59 with an hour at a THI-value of 90, we estimate that the farm-specific annual milk revenues decrease by approximately 0.05% from the farm-specific average milk revenues (indicated by the inner line in red in the top left subpanel in Figure 2) compared to an hour at a THI-value of 47.59. However, this effect is not significant as indicated by the upper confidence band that is not crossing the horizontal 0 line. The confidence bands in Figures 2–4 reveal that there are no significant heat effects on annual milk revenues, veterinary expenses, and feed purchases.[13]

[12]Supporting Information: Section A4 shows the corresponding regression outputs and discusses potential power issues (type II errors). In brief, power is unlikely to be a problem because (i) our sample is comparatively large, (ii) the models identify some parameters that are significantly different from 0, however, the marginal effects of our nonlinear heat variables are not significantly different from zero, and (iii) estimated parameters are larger than minimum detectable slopes.

[13]Point estimates between subsamples may differ because of different knot locations that result from sample-specific knot locations that maximize the goodness of fit. Note that we find no significant marginal effects of our nonlinear heat variables, however, estimated parameters of Equation (1) can be significantly different from zero as highlighted in Supporting Information: Tables A2–A5.

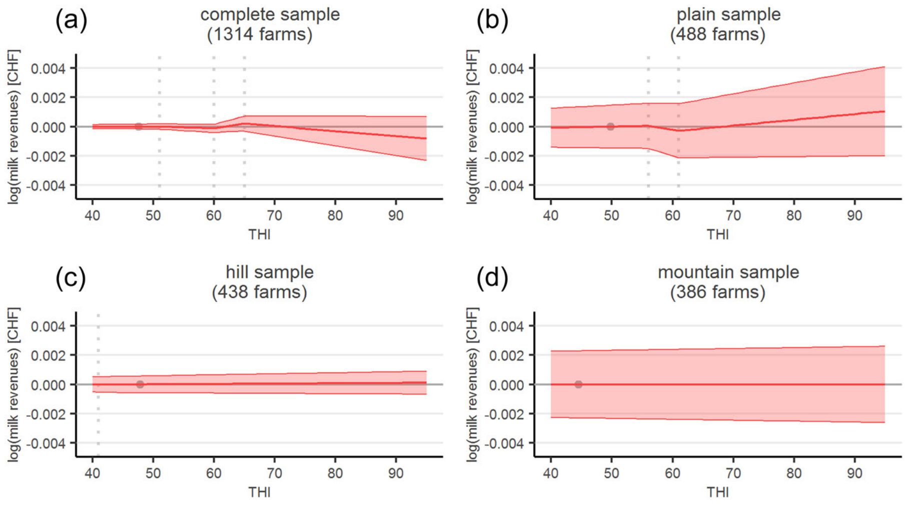


**FIGURE 2** Relative marginal hourly temperature-humidity-index (THI) effects on annual milk revenues for different samples. Curves are centered so that the average THI of the sample has no effect. This point is marked in gray. The upper and lower line in red shows the 95% confidence interval. A 1-hour exposure to the THI-value on the *x*-axis has a significant effect at the 5% significance level if the confidence interval fully crosses the horizontal line in gray. Standard errors are clustered by farms and years. Vertical dotted lines show knot locations. Regression outputs are shown in Supporting Information: Tables A2–A5.

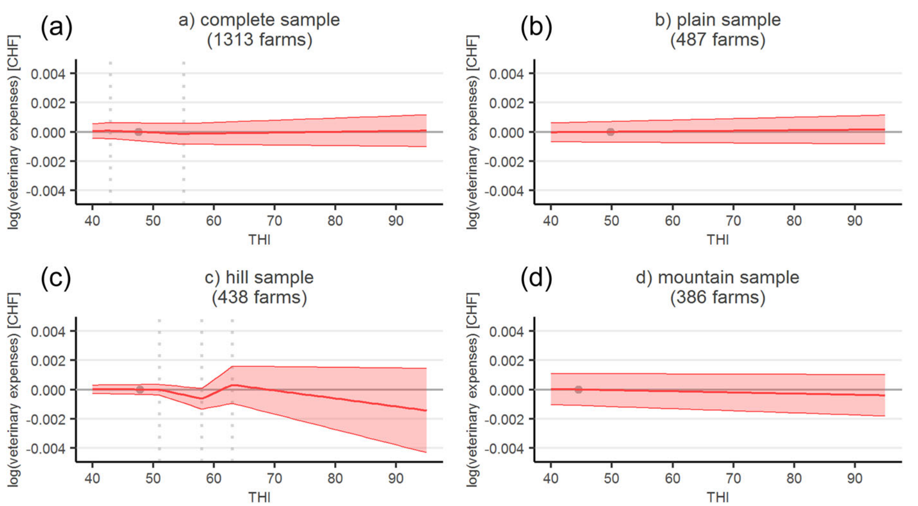


**FIGURE 3** Relative marginal hourly temperature-humidity-index (THI) effects on veterinary expenses for different samples. Curves are centered so that the average THI of the sample has no effect. This point is marked in gray. The upper and lower line in red shows the 95% confidence interval. A 1-hour exposure to the THI-value on the *x*-axis has a significant effect at the 5% significance level if the confidence interval fully crosses the horizontal line in gray. Standard errors are clustered by farms and years. Vertical dotted lines show knot locations. Regression outputs are shown in Supporting Information: Tables A2–A5.

Several robustness checks that address different sample sizes, heat measurements, multicollinearity among variables, milk production intensity, and temporal Alpine milk production in summer confirm our nonsignificant heat effects on annual milk revenues, veterinary expenses, and feed purchases. Supporting Information: Section A5 presents the robustness checks in detail.

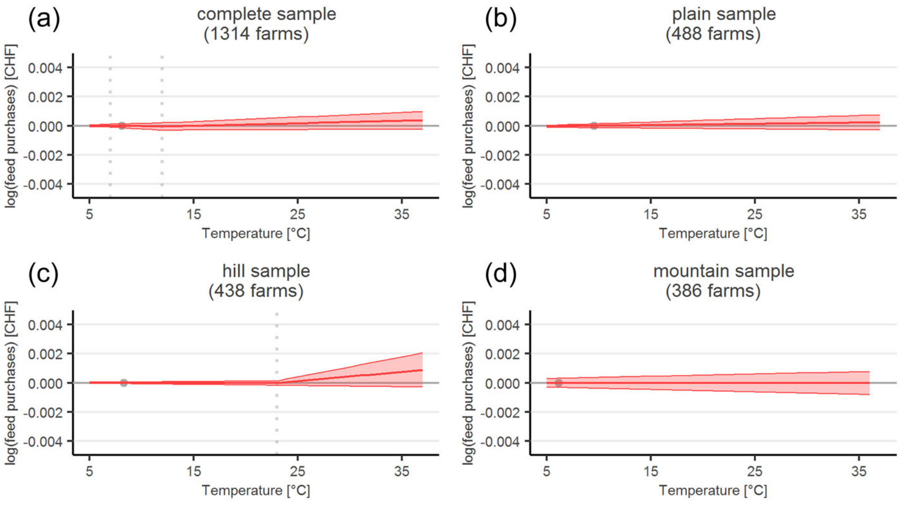


**FIGURE 4** Relative marginal hourly air temperature effects on feed purchases for different samples. Curves are centered so that the sample's average hourly air temperature has no effect. This point is marked in gray. The upper and lower line in red shows the 95% confidence interval. A 1-hour exposure to the temperature value on the *x*-axis has a significant effect at the 5% significance level if the confidence interval fully crosses the horizontal line in gray. Standard errors are clustered by farms and years. Vertical dotted lines show knot locations. Regression outputs are shown in Supporting Information: Tables A2–A5.

## 5 | DISCUSSION

We find no significant heat effects on annually observed milk revenues, veterinary expenses, and feed purchases at farm level for a comparatively large and representative sample of Swiss milk producers. This finding does not result from a potentially low statistical power (see Supporting Information: Section A4) and is confirmed in many robustness checks addressing the sample size, weather data quality, multicollinearity in weather variables, and potentially heterogeneous heat effects. Consequently, annually observed milk revenues, veterinary expenses, and feed purchases are, on average, robust to current heat exposure.[14] However, this does not necessarily mean that Swiss milk producers face no heat-related risks. First, THI-values and temperatures previously identified as harmful (e.g., Bohmanova et al., 2007; Finger et al., 2018; Gammans et al., 2017; Hammami et al., 2013; Ortiz-Bobea et al., 2018; Schlenker & Roberts, 2009) are frequently reached in Switzerland. Second, heat-related risks are increasingly marked due to climate change (e.g., Finger et al., 2010; Zubler et al., 2014). Evidence from regions with more harmful heat exposure (e.g., in the United States [Gisbert-Queral et al., 2021; St-Pierre et al., 2003]) suggests that an increased frequency and severity of heat exposure is likely to affect Swiss milk producers in the future. Thus, it is likely to become more difficult and costly for farmers to cope with increasing heat stress.

The main reasons for the current robustness must be found within farms because a natural hedge between Swiss milk prices and milk production at farm-level is, if there is any, small (see Supporting Information: Section A3.2), and we do not expect heat stress to reduce prices for veterinary services and feed (see also Schaub & Finger, 2020). There exist various sources for robustness to heat stress on the farm and Mayer et al. (1999) find that robust milk production systems can sustain THI-values of up to 87 without a loss in well-managed systems. Robustness can

[14]The results show that there are no heat effects on the majority of Swiss milk producers. This does not exclude possible heat effects on some farms, but the number of such farms, if there were any, would be small.

result from the capacity of a system to withstand heat stress (Meuwissen et al., 2019). This may include heat-tolerant species in pastures and heat-tolerant breeds of cows, a low production intensity or the use of ventilated facilities, shade-providing trees in pastures, large stocks of feed to buffer shortages, or the use of cool Alpine pastures in summer (e.g., Lee et al., 2013; Mack et al., 2013; Nardone et al., 2010; West, 2003). Another source of robustness is adaptability, that is, the capacity of a system to respond to heat stress by adapting management practices (Meuwissen et al., 2019). These adjustments in management practices may include the activation of fans or sprinklers, adjustments in nutritional management (e.g., grazing strategy and provision of cooled water), adjustments in herd compositions, or activation of irrigation systems in pastures or feed crops (Chang-Fung-Martel et al., 2017; Finger et al., 2018; West, 2003). Insurance solutions could also complement adjustments in management practices and buffer financial losses after heat exposure (Deng et al., 2007; Vroege et al., 2019).

Our model offers many advantages that support the identification of overall heat effects as highlighted in Section 2 (see also Auffhammer, 2018; Blanc & Schlenker, 2017; Hsiang, 2016; Schlenker & Roberts, 2009). However, the model is based on two assumptions and faces potential limitations. It assumes time separability of weather variables and that the effects of different weather variables (here precipitation and THI or air temperature) are separable. A limitation of our model is that a reduced-form model cannot show the exact ways in which heat would affect annual milk revenues, veterinary expenses, and feed purchases. In addition to this, we can neither identify the determinants of the identified robustness (i.e., factors that mitigate heat effects) nor quantify by how much the identified robustness results from a general robustness to heat stress (e.g., heat-tolerant breeds) and by how much the observed robustness results from short-term management adaptations (e.g., activation of ventilation systems). However, our aim is to identify overall heat effects on the dependent variables and not to identify exact mechanisms or reasons for the robustness. Another limitation is that our model only considers within-year heat stress and does not consider heat stress of the previous year. However, Swiss winters are cold and give cows and pastures time to recover from heat stress in warmer months so that we do not expect relevant effects from the previous year. Potential effects of cold stress and their mechanisms are an interesting opportunity for future research, but this requires another thermal measurement than the THI, which was calibrated for heat stress only. Additionally, we focus on annually observed milk revenues, veterinary expenses, and feed purchases at farm level because these economic variables are of highest relevance for farmers. However, this does not exclude potential heat effects on less aggregated dependent variables (e.g., monthly milk revenues/quantity of a single cow). Another limitation is the use of farm and year-fixed effects that may absorb some heat effects. However, the fixed effects control for many relevant confounders such as soil quality, technological trends, and (often abrupt) changes in agricultural policy and markets. Finally, measurement errors in the weather data might bias our estimated heat effects. However, we use weather data of highest available quality that minimizes measurement errors and our results are robust to the use of different heat measurements. Thus, we might miss heat effects of small economic relevance but are unlikely to miss heat effects that are of substantial economic relevance.

## 6 | CONCLUSION

This paper identifies overall heat effects on annual milk revenues and for the first time also on annual veterinary expenses and feed purchases at the farm level. These three accountancy variables are key drivers of the profitability of milk production. We estimate these overall heat effects for milk producers in Switzerland by combining farm accountancy data with high-quality weather data in a model that captures overall heat effects, that is, a model that accounts for all the various and interrelated ways in which heat exposure may affect the three accountancy variables and that accounts for endogenous adaptation measures. Although potentially harmful heat exposure is frequently observed, we do not find significant heat effects on annual milk revenues, veterinary expenses, and feed purchases.

This implies that Swiss milk producers, on average, are robust to current heat stress in terms of annual milk revenues, veterinary expenses, and feed purchases. However, ongoing climate change disproportionately affects the Alpine region so that heat exposure is likely to become more frequent and severe in the future. Therefore, milk producers should be aware of increasing heat stress and increase their robustness if necessary. Policymakers can support this by establishing a political environment that incentivizes both mitigation and adaptation measures and by supporting research that aims to develop tools to cope with increasing heat stress.

Future research should estimate weather effects not only on revenues but also on production costs because production costs can also be affected by weather conditions and drive profit variability. This should also entail the identification of exact mechanisms and factors that influence weather impacts on milk production. Since the robustness of milk production systems varies, research should quantify heat effects also in other regions to assess the vulnerability of different systems, support adaptation to ongoing climate change, and advise policymakers. Finally, the improvement of heat risk management under consideration of economic feasibility and animal welfare opens an interesting field for future research.

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## DATA AVAILABILITY STATEMENT

Data used are described in the main text and online appendix. Farm-level accountancy data are owned by the Swiss Confederation center of excellence for agricultural research (Agroscope) and all weather data by the Federal Office of Meteorology and Climatology (MeteoSwiss). All codes are published on GitHub: https://github.com/AECP-ETHZ/Heat-Risks-in-Swiss-Milk-Production.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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