The Impact of Local Heat Extremes on the Performance of Dairy Processing Firms in Europe

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Abstract

We estimate the impact of local temperature-humidity (THI) shocks, which are known to affect dairy production at the farm-level, on dairy processors' profits in Europe. We hypothesize that especially smaller dairy processors have little market power and are unable to shift heat related cost increases in their raw milk supply downstream. We use data on 1'606 firms in the ORBIS database from 2011-2019 (12'643 total observations). Along various robustness checks, we consistently find that local heat extremes have no significant effect on the profits of dairy processing firms. Our findings suggest that heat induced losses remain at the farm level, which provides important implications for policy makers, the dairy industry, and farmers on who is (not) affected by extreme weather.

Keywords: heat; risk; temperature-humidity index; profitability; dairy

1 Introduction

With increasing average earth surface temperature the magnitude and frequency of heat extremes is expected to increase (IPCC, 2014). In Europe, the rate of warming is even beyond the global average, and Europe has been one of the regions that experienced the strongest heat extremes since the 1950s in recent years (European Environment Agency, 2020; Suarez-Gutierrez et al., 2018). Earlier research shows that dairy farming is particularly vulnerable to hot weather (Qi et al., 2015; Finger et al., 2018). Heat stress can increase the incidence of cow diseases and influence cows' reproduction, thus affecting milk production (Bohmanova et al., 2007; M. Rhoads et al., 2009). These impacts can result in fluctuations of farm profits (St-Pierre et al., 2003). Moreover, the profit shock at the farm level likely affects dairy processors' profits through increasing raw milk prices, decreasing milk quality, and shifts in consumer demand. In Europe, the dairy industry is one of the most important food industries and represents more than 12% of the total agricultural output (Augere-Granier, 2018). Thus, understanding the potential impact of heat on the dairy economy in Europe is crucial. Although the economic impact of weather extremes on livestock farms has been well documented (Lane et al., 2019; Mayer et al., 1999), little research has focused on the impact on the dairy processing industry.

In this paper we quantify the impact of local heat shocks on dairy processors' profits in Europe, so as to provide decision support for this industry and a climate vulnerability assessment for policy makers. We put a particular emphasis on the impact of heat shocks on the profits of smaller dairy processors. Particularly, smaller dairy processors are hypothesized to not have sufficient market power to shift heat related cost increases to food retailers. A better understanding of climatic vulnerability provides crucial decision support for dairy firms to avoid profit losses. Moreover, knowing these effects helps dairy processors adapt to climate change and policy maker to identify where climate change will hit the food production system.

We use fixed effects panel regression to study the impact of random and exogenous heat shocks on the profits of dairy processing firms in Europe. Our model specification allows to estimate causal effects of a heat shock, which is a deviation from the average heat exposure of a dairy processor with respect to the average exposure at the production location over the years and to the average exposure of all other firms in a given year. We thus control for all time-invariant confounding variables and all systemic factors (Firebaugh et al., 2013, Blanc & Schlenker, 2017). In line with earlier research focusing on heat extremes in livestock, this paper applies the Temperature-Humidity Index (THI) to measure heat stress (Dash et al., 2016; St-Pierre et al., 2003). Heat extremes are denoted by the number of days that daily maximum THI at a firm's production location is higher than $THI_{threshold}$ for each firm in each year during the study period. $THI_{threshold}$ is a threshold value of THI above which heat extremes are expected to be harmful for dairy cows. To put a particular emphasis on extreme conditions, this paper chooses 80 as the THI threshold value, which, for instance, could be a combination of temperature of 30 degrees Celsius and relative humidity of 61%. In various robustness checks, we systematically change the specification of our regression model along firm size and regional subsamples, the definition of heat, and the definition of profits. We use panel data on dairy processors' profits and firm characteristics as provided by the ORBIS database, which is a comprehensive data resource on private companies worldwide (Orbis, 2021). The data is collected from 1'606 European firms observed from 2011 to 2019, resulting in 12'643 observations in total. To complement the economic data with weather conditions, we excluded those firms from the sample that did not provide spatial coordinates of their production location. Using the spatial location we matched the economic data with historical weather records from two climate databases, Agri4Cast Resources Portal and European Climate Assessment & Dataset (Agri4cast, 2021; ECA&D, 2020).

In contrast to our hypothesis, we find no significant impact of heat extremes on the profitability of dairy processing firms in Europe, indicating that the profit shock at the farm level is not transmitted from farms to dairy processors. The results remain robust to different profit proxies (turnover, ROE), $THI_{threshold}$ values (75, 80, 85), firm sizes (micro, small, medium, large), and geographic regions (east, west, north, south). This implies that even small dairy processing companies have sufficient market power to avoid sharing farmers' heat risk. This delivers important implications for climate change adaptation, since losses occur mainly at the farm level.

The remainder of this paper are structured as follows. First, we provide background information on the livestock physiological consequences of heat stress in dairy cows. Based on this we develop our hypotheses how dairy processors can be affected by local heat extremes. Next, we describe the economic and weather data as well as our regression model and identification strategy. After that, we present our results and end the paper with a discussion and conclusion with implications for policy makers, dairy processors and future research.

2 Background

2.1 Impact of heat extremes on dairy production

It has been found that heat extremes have significant impacts on dairy cows in multiple studies. These impacts can be categorized as (1) the impacts on cow health (2) the impacts on cow reproduction (3) the impacts on milk production. And all of these effects can thus lead to changes in various dairy products in terms of quantity and quality (Cowley et al., 2015).

Impacts on cow health

The impacts of heat extremes on cow health can be both direct and indirect. Heat extremes can directly affect the cow's physiology, metabolism, hormonal, immune, and endocrine system, leading to temperature-related illness and death (Das et al., 2016). Specifically, high temperature affects the physiological mechanisms of cows' rumen, increasing the risks of metabolic disorders (Nardone et al., 2010). Plus, heat stress also causes hypothyroidism and affects the animal's metabolic pattern (Helal et al., 2010). Besides, in the hot environment, animals tend to increase their respiration rate and sweating, which leads to the loss of body fluids and may cause respiratory alkalosis (Benjamin, 1961). In addition, Giesecke (1985) finds that the incidence of new udder infections and mastitis will increase due to insufficient breast defense mechanisms in hot weather. Moreover, heat stress decreases the cow's blood glucose and does harm to the immune system, resulting in the incidence of health problems such as liver lipidosis and impaired liver function (Basiricò et al., 2009).

The indirect impacts of heat waves on cow health are mainly conducted through feeding behavior. For one thing, the rise in ambient temperature has a negative influence on the appetite center of the hypothalamus, thereby reducing feed intake (Baile & Forbes, 1974; R. P. Rhoads et al., 2013). For another, the heat gain of feed is an important source of heat production for ruminants, so cows usually reduce feed intake to reduce heat production in a warm environment (Kadzere et al., 2002). According to the research from Lacetera et al. (1996), the risk of subclinical or clinical ketosis in high-yielding cows in summer can increase due to the reduced feed intake. Plus, increasing intake of concentrates and decreasing forage intake can exacerbate acidosis, resulting in the occurrence of lameness in cows (Lacetera et al., 1996). Besides the changes in feeding behavior, high temperature and humidity give a good living environment for microorganisms and parasites, which may cause some zoonotic diseases and foodborne infections (van der Spiegel et al., 2012).

Impacts on cow reproduction

One of the most important effects of the heat extremes for dairy farmers is reproduction impairment. Generally, heat stress reduces the intensity and length of cows' estrus behavior, leading to a decrease in reproductive performance (Hansen et al., 2001; Salah & Mogawer, 1990). For female cattle, heat stress affects the development of follicles and embryos (Campen et al., 2018). Sakatani et al. (2014) estimates the influence of heat stress on fertilization by an in vitro model and find that heatwaves cause oxidative stress, hindering the further development of the zygote. Besides, in the hot atmosphere, the fetus is malnourished, which eventually leads to fetal growth retardation (Tao & Dahl, 2013). For male cattle, heat stress harms sperm quality and DNA integrity (Malama et al., 2016).

Impacts on milk production

Research on the impact of high temperature and humidity exposure on dairy production shows a consistently negative effect on milk quality and quantity. For instance, Bouraoui et al. (2002) quantify the impacts of heat stress (using the temperature-humidty-inde THI) and find that the correlation coefficient between daily THI and milk yield is -0.76. The milk yield decreases by 21% when the THI value increases from 68 to 78. Moreover, St-Pierre et al. (2003) estimate the annual milk yield loss caused by heat stress and show that reduction in milk production varied in different regions in the United States, ranging from 86 to 2072 kilograms per cow per year. In addition, Gaafar et al. (2011) report that total milk yield declines by 39% when THI value increases from 59.82 to 78.53.

There are several reasons for the decline in milk production due to heat extremes, two of which are the above-mentioned negative effects on cow health and reproduction. Besides them, declined feed intake is also an important factor in reducing milk yield (Baumgard & Rhoads, 2013). For every 1°C increase in temperature above a cow's thermoneutral zone (TNZ), dry matter intake (DMI) will be reduced by 0.85 kilograms, and this reduction in intake accounts for around 35% of the decline in milk production (M. Rhoads et al., 2009; West, 2003). High-yielding dairy cows are particularly vulnerable to heat extremes because the higher yield, the stronger the negative relationship between heat and feed intake (Lane et al., 2019).

Heat extremes affect not only milk yield but also milk quality. For one thing, the milk composition can be affected (West, 2003). For example, heat stress can reduce protein, fat, and casein content (Cowley et al., 2015; Kadzere et al., 2002). For another, in climate change, the feedstuffs have a high probability to be polluted by aflatoxin which can be transferred to milk (Paterson & Lima, 2010; Prandini et al., 2009).

Economic impacts on the dairy farms

Research on the economic impacts of heat extremes on the dairy sector is so far entirely focused on the farm level.. The negative effects on cow health, reproduction, and milk production impact dairy farms economic performance in different ways. Overall, these effects increase profit fluctuations of dairy farms (Alan Rotz et al., 2016). Mayer et al. (1999) use a find that losses of an example dairy farm in Australia can vary from $6838 to $11986 per year. St-Pierre et al. (2003) calculate capital and operation costs for the dairy industry under four intensities of heat abatement, which are minimum, moderate, high, and intensive respectively. They find that without heat abatement, heat stress could result in $897 to $1500 million loss for the dairy industry across the United States per year. Finger et al. (2018) find that heat induced losses of German dairy farmers can exceed 25,000 EUR per farm. In addition, Key and Sneeringer (2014) find that heat extremes reduce the technical efficiency of dairy farms. In order to mitigate thermal stress, farmers can apply risk management practices and install cooling systems for cows, which tend to increase operation costs (Key & Sneeringer, 2014).

Although the economic impacts of heat extremes on dairy farms have been discussed a lot, there is no research on the impact of heat extremes on the profits of dairy processors so far to the best of our knowledge.

2.2 How heat extremes can affect dairy processors

Local heat extremes at the production location can affect profits of dairy processors through three channels (mechanisms). First, heat extremes can cause production shocks at the dairy farm level, causing local shortages of raw milk supply. Depending on the market integration of the production region the resulting change in the market equilibrium between farms and dairy processors might increase the input price (for raw milk) for the dairy processors (Key & Sneeringer, 2014). Thus, the profit shock of the dairy processor depends on how much price change can be transmitted from the farm to the firm. Thereby, the profits of both dairy farms and processors would probably be affected due to the milk production shocks. Second, heat exposure affects milk quality components at the farm level such as fat and protein content of the milk. In addition to volumetric raw milk shortages this can cause an additional lack of supply in high quality milk, which itself can affect the quality of processed dairy products. Third, local heat extremes might affect consumer demand for dairy products. Although we hypothesize the demand channel to affect how local heat shocks translate into profit shocks of dairy processors, we are not aware of any literature in this direction.

The characteristic of the dairy industry also sets the stage for such mechanisms between heat extremes and the profits of dairy processors. To be specific, the collection and transportation of milk are costly, often accounting for over 30% of milk processing costs (FAO, 2021). Dairy processors tend to shorten the transportation distance to save costs because the total expense has a positive correlation with the transportation distance (Thirupathi et al., 2020). Therefore, the activities between dairy farms and dairy processing firms are usually limited in a very regional market as a result of cost minimization. This makes the dairy processors potentially sensitive to the local weather conditions. Therefore, we expect these mechanisms to be particularly important for smaller processing companies that tend to purchase their raw milk and sell their processed products more closely to their production location. We use the European Commission's firm-size classification into micro-, small-, medium-, and large-sized firms according to their number of employees (see section *3.2 Data* for more info). Moreover, we assume that smaller dairy processors, who purchase their raw milk locally, possess sufficient market power to shift heat related cost increases downstream to food retailers.

3 Methods and data

Although we expect the channels described in section 2 to be the key mechanisms between heat shocks and dairy processors' profits, we are unable to observe them. We therefore estimate a reduced form model to quantify the impact of local heat shocks at the production location on dairy processors' profits. The reduced form model does not assume any theory-based structural relationships among variables, instead, it can directly show the relationship among variables based on historical data (Kolstad & Moore, 2020). We use unit and time fixed effects to identify causal links between local heat shocks and dairy processors' profit shocks based on historical weather and profit data.

3.1 Regression analysis

Fixed effects models have been widely used to quantify the effects of random and exogenous weather shocks on agricultural production (e.g. Dalhaus et al., 2020; Hirvonen, 2016). The typical advantage of fixed effects models in this context is that they can alleviate omitted-variable bias because fixed effects allow controlling for unobserved time-invariant factors and market wide factors (Firebaugh et al., 2013; Kolstad & Moore, 2020). More specifically, we model local heat shocks as deviation from the average heat exposure at the firm location and from the average heat exposure of all other firms in a given year. Similarly, our fixed effects specification allows to look at profit shocks which are again deviations from the single firms average profits and the average of all other firms in a given year. Therefore, we can estimate the causal effect of heat extremes on dairy processors' profits in Europe. We thus estimate the following model:

$$\log(TO_{it}) = \beta\, THI_{it} + c_i + \gamma_t + \varepsilon_{it} \tag{1}$$

where $\log(TO_{it})$ is the turnover of firm *i* in year *t*, which we use as a proxy for profits. β gives the marginal impact of a shock in the temperature humidity exposure THI_{it} at firm *i* in year *t* (See next section on an explanation of the THI). Additionally, we proxy profits using the return on equity (ROE) as a robustness check. c_i and γ_t capture firm fixed effects and time fixed effects respectively. More specifically, c_i capture all unobserved time-invariant firm characteristics such as the abilities of the firms' managers, or location specific factors. T_t absorb systemic time effects that are constant for all firms such as the European-wide market price of dairy products. ε_{it} is the error term. To allow for heteroscedasticity and spatial and temporal correlation of the errors, standard errors are heteroscedasticity robust and double clustered by firm and year

We provide all data and code at (XXX github link will be added after publication) to fully replicate our results.

3.2 Data

Firm profit data

The panel data of profits of dairy processing firms in Europe from the year 2011 to 2019 are gathered from the ORBIS database which is a powerful global data resource. The ORBIS database captures a wide variety of firm performance data and firm characteristics, of which we use the turnover and ROE and subset for firms in Europe that operate in the dairy processing industry, as defined by NACE code C1050 ("Manufacture of dairy products"). Many studies have used the ORBIS database to find, analyze, and compare the profitability performance of different companies (e.g. Luptak et al., 2015; Ribeiro et al., 2010). In this paper, we use the turnover and Return on Equity (ROE) as proxy for a firm's profit. For matching the economic data with weather variables, we need the firms location information as spatial coordinates. Therefore, we removed the firm observations that did not include coordinate information, which results in 1'606 dairy processing firms. The locations of these firms cover 28N-68N and 16W-60E, which can be seen in ***Figure 1***. Black dots are the locations of the 1'606 dairy processing firms, which are mainly concentrated in western and eastern Europe. Unfortunately, removing those firms that did not provide spatial coordinates systematically removes central European countries from the sample. We tried to recover the location information for these firms based on their firm address, which howeder led to unreasonable spatial coordinates. We therefore included only those firms and countries for which we had spatial coordinates and clearly indicate this as a potential limitation of our study.

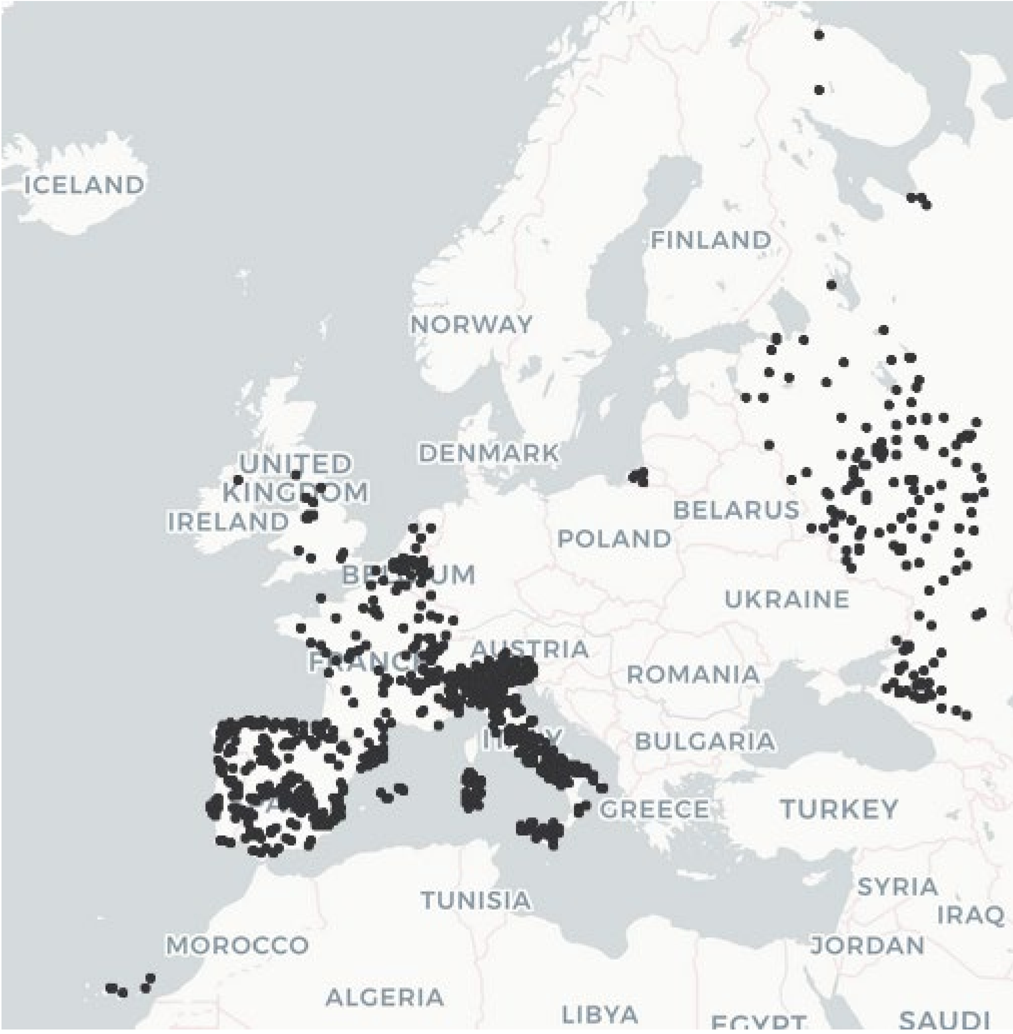

Figure 1: The locations of the dairy processing firms included in panel regression

Since we expect different results for differently sized companies, we additionally obtained the number of employees from the ORBIS database and classified the firms into four different size classes based on the European Commission standard procedure (European Commision, 2016). Firms with 1-9 employed are micro-sized firms, which are denoted by size 1 in this study; Firms with 10-49 persons employed are small-sized firms, which are denoted by size 2; Firms with 50-249 persons employed are medium-sized firms, which are denoted by size 3; Firms with 250 and above persons employed are large-sized firms, which are denoted by size 4. Figure 2 gives an overview of the number of observations in each size class.

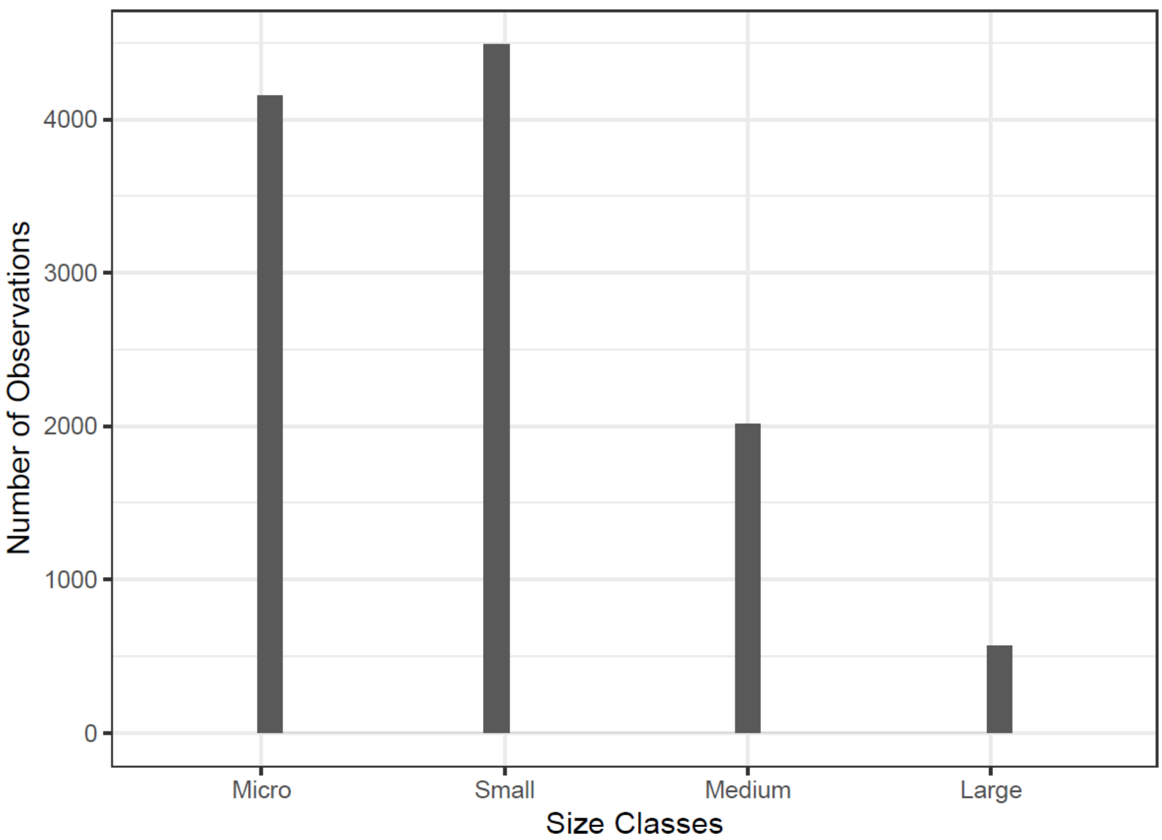

Figure 2: Histogram of company size classes according to the number of employees

Weather data

The most widely used index for heat-related animal stress is the Temperature-Humidity Index (THI) (Deng et al., 2007; Gaughan et al., 1999; Ingraham et al., 1974). THI comprehensively considers the combined effects of dry-bulb temperature, wet-bulb temperature, and relative humidity. A number of models have been developed to formulate THI (Dikmen & Hansen, 2009). The use of THIs varies according to the different climate conditions. In humid climates, THI with a greater weight for humidity is more appropriate, while the indices with a greater weight for ambient temperature work best under semiarid climates (Dash et al., 2016). From Bohmanova et al. (2007), we use a THI designed to represent the heat stress for outdoor cows and which is applicable to the majority of European production locations and which is calculated as follows:

$$THI = (1.8T_{db}+32) - (0.55 - 0.0055RH) * (1.8T_{db} - 26) \quad (2)$$

where T_{db} denotes dry bulb temperature (in degrees Celsius) and RH represents relative humidity (in percentage).

Data of daily maximum temperature and daily mean relative humidity at the firm location are needed to calculate THI. Historical data of daily temperature are collected from Agri4Cast Resources Portal which is a meteorological dataset from European Commission (Agri4cast, 2021). Relative humidity can be calculated from vapor pressure and mean temperature (Stull, 2020). The formulas are as follows.

$$relative\ humidity = water\ vapor\ pressure / saturation\ vapor\ pressure * 100 \quad (3)$$

$$saturation\ vapor\ pressure = e_0 * [L/R_v * (1/T_0 - 1/T)] \quad (4)$$

where e_0 is the saturation vapor pressure at 0 degrees Celsius; L is the latent heat of vaporization which equals $2.5\text{x}10^6$ $J \cdot kg^{-1}$ here; R_v is the water-vapor gas constant and equals to 461 $J \cdot K^{-1} \cdot kg^{-1}$; T_0 is 0 degrees Celsius and T is the mean temperature we obtained.

Heat extremes are then denoted by the number of days that daily maximum THI at a firm's production location is higher than $THI_{threshold}$ for each firm in each year during the study period. $THI_{threshold}$ is a threshold value of THI above which heat extremes are expected to be harmful for dairy cows. We use a $THI_{threshold}$ of 80 in our main specification and a $THI_{threshold}$ of 75 and 85 as robustness checks.

Historical data of daily water vapor pressure are collected from Agri4Cast Resources Portal as well. All these weather data match the locations of each dairy processing firm in this study, and we get 12’643 observations for panel regression in total. See descriptive statistics in ***Table 1***.

Table 1: Descriptive statistics

Variables	Minimum	Median	Mean	SD	Maximum
Turnover [kEUR]	0	3’391	43’516	419’751.3	15’778’283
ROE	-927	3.45	4.19	49.27	868.49
THI days (75)	0	93	82.65	39.22	186
THI days (80)	0	36	37.41	27.98	139
THI days (85)	0	2	6.68	10.43	73
No. of employees	1	14	51.76	101.58	824

4 Results

In figure 3 we show coefficient plots of the marginal impact of a one-day THI exposure according to our main specification of THI 80 and two robustness checks using THI 75 and THI 85 on the turnover of dairy processing firms. In contrast to our hypothesis, we do not find any impact of temperature-humidity shocks on turnover shocks in the European dairy industry that is significantly different from zero. Moreover, figure 4 shows a similar pattern for the impact of temperature-humidity shocks on return on equity (ROE) shocks. Full regression results with diagnostics of all models included in figures 3 and 4 can be found in the online appendix.

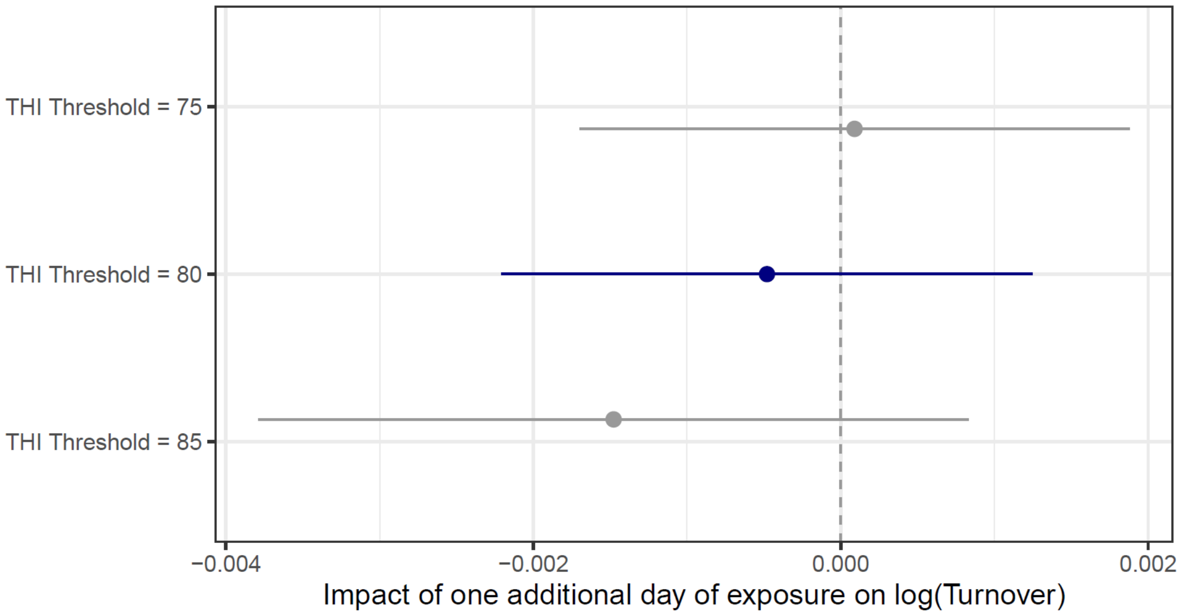

Figure 3: Coefficient plot of the impact of the exposure to one additional day with a daily maximum THI larger than 80 (blue, main specification), 75, and 85 (grey robustness checks) on log(Turnover) based on individual regressions. 99% confidence intervals are based on double clustered standard errors**.** Full regression results including model diagnostics are available in the online appendix

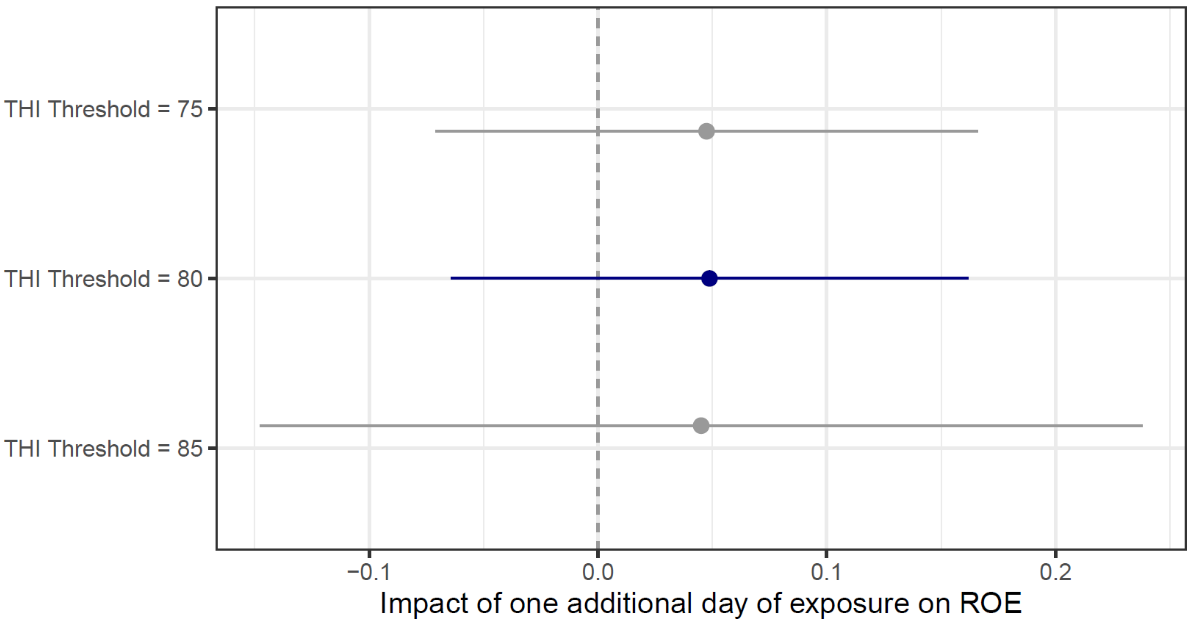

Figure 4: Coefficient plot of the impact of the exposure to one additional day with a daily maximum THI larger than 80 (blue, main specification), 75, and 85 (grey robustness checks) on ROE based on individual regressions. 99% confidence intervals are based on double clustered standard errors. Full regression results including model diagnostics are available in the online appendix

We follow Schlenker and Roberts (2009) and conduct a robustness check by dividing the sample into four spatial subsamples based on median coordinates and running subsample models. Specifically, we choose the mean longitude (10.3 E) of all the dairy processors as the dividing line between western and eastern Europe; and similarly, we choose the mean latitude (44.5 N) as the dividing line between northern and southern Europe. Then we run the same regression model again on turnover and ROE for all three different $THI_{threshold}$ values. As shown in the coefficient plot figures 5 and 6, the estimates across spatial sub-samples are consistently found to be not significantly different from zero at the 99% confidence level. Therefore, we do not find that a particular spatial subset is driving the overall results. Instead the impact of heat shocks is consistently not significantly different from zero over the whole study region.

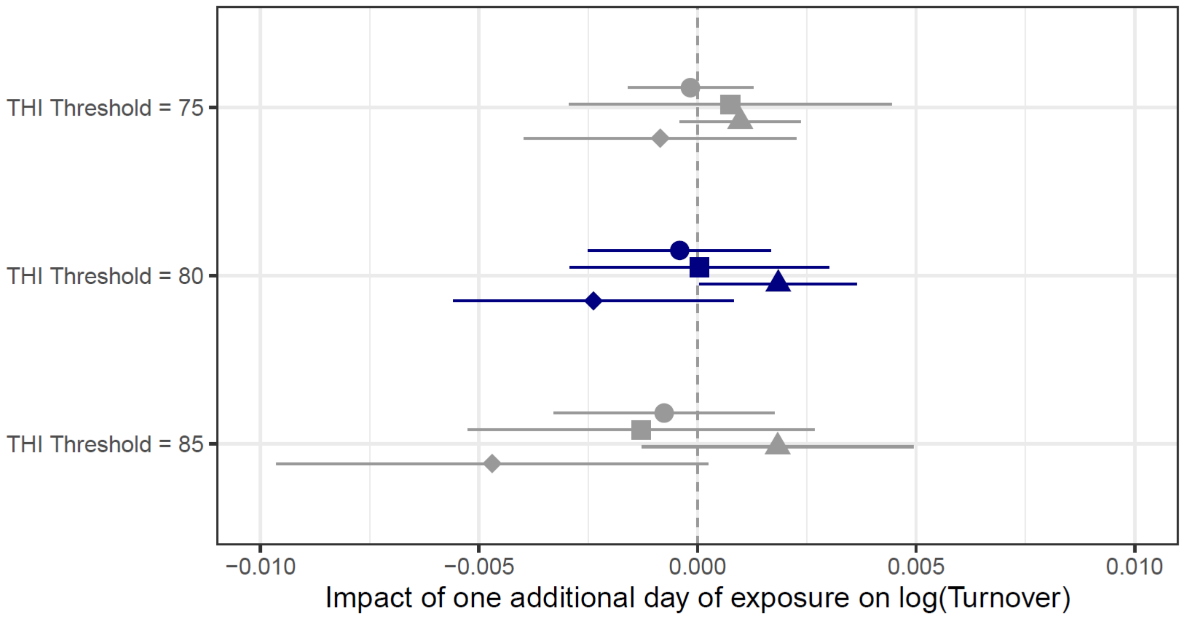

Figure 5: Coefficient plot of the impact of the exposure to one additional day with a daily maximum THI larger than 80 (blue, main specification), 75, and 85 (grey robustness checks) on log(Turnover) based on individual regression models. 99% confidence intervals are based on double clustered standard errors. Different point shapes indicate spatial subsamples (● = south, ■ = north, ▲ = west, ♦ = east). Full regression results are available in the online appendix.

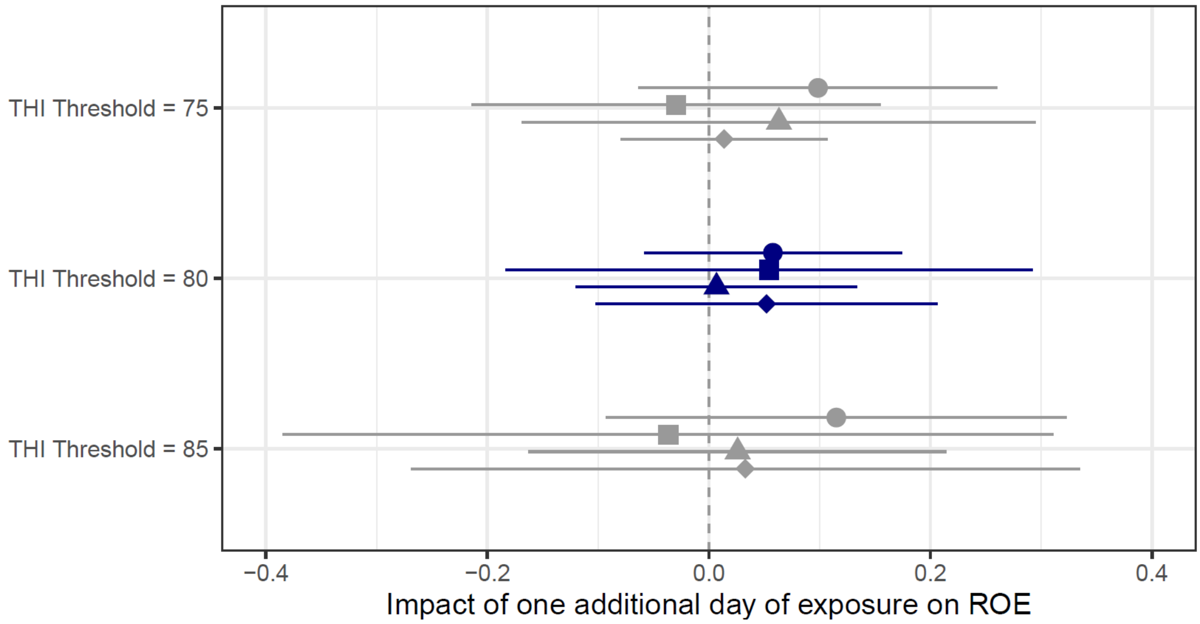

Figure 6: Coefficient plot of the impact of the exposure to one additional day with a daily maximum THI larger than 80 (blue, main specification), 75, and 85 (grey robustness checks) on log(Turnover) based on individual regression models. 99% confidence intervals are based on double clustered standard errors. Different point shapes indicate spatial subsamples (● = south, ■ = north, ▲ = west, ♦ = east). Full regression results including model diagnostics are available in the online appendix.

According to our hypothesis of smaller dairy processors being stronger affected by local heat shocks that affect their local suppliers, we run our regression analysis for different size class sub samples (proxied by the number of employees) both using turnover and ROE as dependent variables separately. As shown in figures 7 and 8, we do not find any significant impact of heat shock on dairy processors' performance shocks at the 99% confidence level.

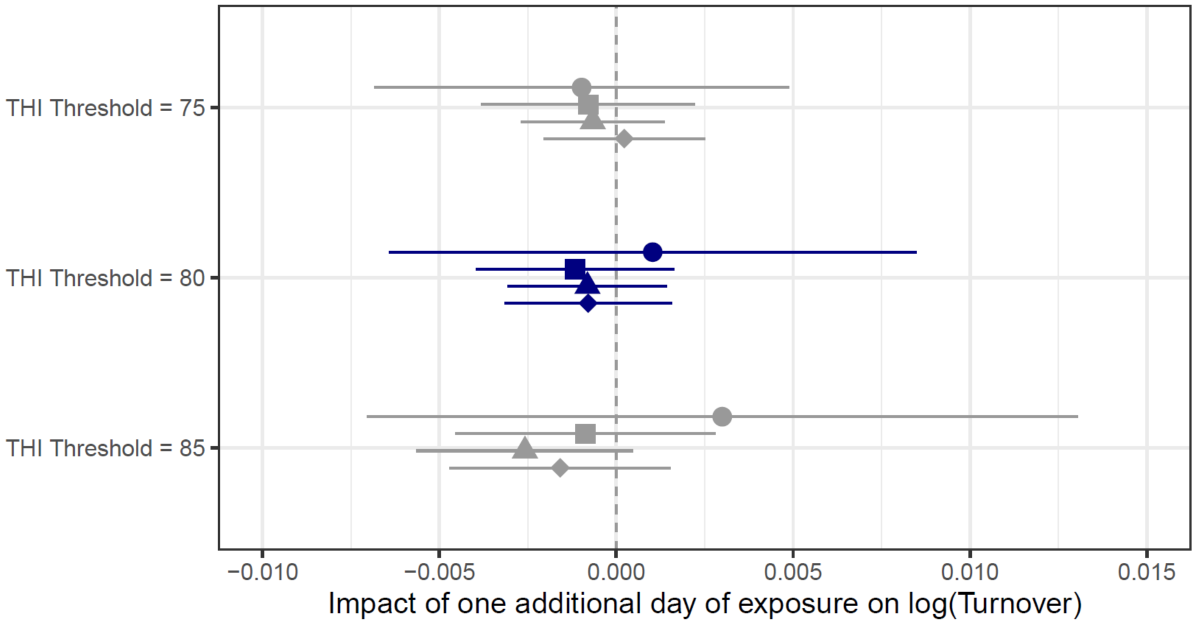

Figure 7: Coefficient plot of the impact of the exposure to one additional day with a daily maximum THI larger than 80 (blue, main specification), 75, and 85 (grey robustness checks) on log(Turnover) based on individual regression models. 99% confidence intervals are based on double clustered standard errors. Different point shapes indicate firm size sub samples (● = large, ■ = medium, ▲ = small, ♦ = micro). Full regression results are available in the online appendix.

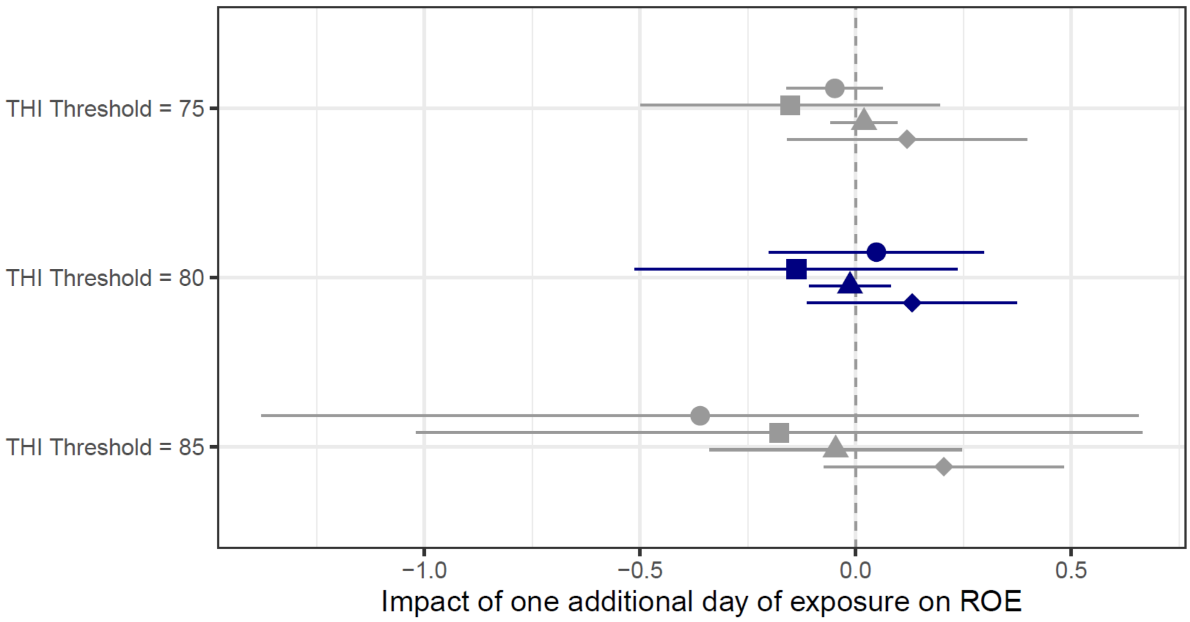

Figure 1: Coefficient plot of the impact of the exposure to one additional day with a daily maximum THI larger than 80 (blue, main specification), 75, and 85 (grey robustness checks) on ROE based on individual regression results. 99% confidence intervals are based on double clustered standard errors. Different point shapes indicate firm size sub samples (● = large, ■ = medium, ▲ = small, ♦ = micro). Full regression results are available from the appendix.

Summing up our results, we consistently find that local heat extremes have no significant impact on the profits of dairy processing firms, which is not in line with our hypothesis. The results are robust to the changes in the profit indicator, $THI_{threshold}$, spatial sub-samples, and firm sizes.

5 Discussion

Previous research has well documented the economic losses of heat extremes on dairy farms (e.g. Rotz et al., 2016; St-Pierre et al., 2003). However, it was unclear how local heat shocks affect dairy processing firms, which closely rely on local farmers' raw milk supply. This study fills this knowledge gap by estimating the impacts of heat extremes on dairy processors' profits in Europe using a rich sample of dairy processors' economic performance data, environmental conditions on temperature and humidity exposure and regression analysis.

Our regression results robustly show that local heat shocks have no significant impact on the profits of dairy processing firms, regardless of the size of the firm and the spatial location within Europe, the definition of heat extremes, and the proxy for profit. These null results suggest that the economic losses caused by local heat extremes at the farm level are not transmitted from dairy farms to processing stages in Europe. In other words, dairy processors tend to be better able to cope with climatic shocks than farmers. Although we are unable to observe dairy processors' management, literature suggests that a reason for this could be that dairy processors have a more professional business system and better risk management abilities (Schaper et al., 2009). To be specific, business experts in dairy firms can improve firm performance by adjusting sales and marketing strategies in crisis times (Panagopoulos & Avlonitis, 2010). For example, when the sales of dairy products decrease, dairy processors can post advertisements or provide discounts to increase consumption and profits (Akaichi et al., 2015; Malik et al., 2013). Besides, dairy processing firms have the ability to develop diverse innovative products (such as new flavor ice-cream in summer) to increase revenues (Gilbert et al., 2016). However, dairy farms have a limited abilities to alter production practices, which increases the risks of income losses when the cows are impacted by heat extremes (Geiger, 2018; St-Pierre et al., 2003). Although dairy farms have the possibilities to manage weather risks by, for instance, installing shading systems and air cooling machines (Fournel et al., 2017), dairy processors seem to have better opportunities to reduce climatic risks. Additionally, dairy processors can have more time to react to weather risks as farms are the first ones in this supply chain directly affected by weather extremes. When the weather extremes affect the production of dairy farms, the processors can observe that in time and take pre-actions to avoid losses (Cropp & Zijlstra, 2007). Finally, while heat extremes can affect the raw milk quality in terms of fat and protein content dairy processors can buffer this risk with pricing mechanisms that reward high and punish low contents of valuable constituents. The resulting cost savings can be spent on heat related management (such as marketing). In the milk market, dairy farmers are price takers while processors are (at least partly) price makers (Chrisman, 2019). Dairy processors have the right to pay less for the lower quality milk (Watters & Zurakowski, 2018, FrieslandCampina, 2021).

Although our regression model is well established in the literature on weather shock impacts and we use rich datasets on weather and economic performance, we would like to point towards three possible limitations of our work. First, the dataset covers only parts of Europe. More specifically, we had to exclude those dairy processing firms that did not provide spatial coordinates of their production sites, which systematically excluded key players in the European dairy market. For example, we do not have information on German dairy processing firms, while Germany is the largest dairy producer in Europe and processes about one-fifth of the dairy products in Europe (Eurostat, 2021). If data becomes available, future research is advised include the large dairy-producing countries in central Europe. Second, we proxy heat extremes by the number of days that daily maximum THI is above a specific threshold. This could be extended by applying the idea of "degree days" to calculate how long and how much THI exceeds the threshold value (Christenson et al., 2006; Dalhaus et al., 2020), allowing for estimating the impact of a hourly exposure to different THI levels. However, since we do not find any significant impact of the here used THI proxy we do not expect our results to change. Third, this study applies a reduced-form model to directly show the relationship between weather extremes and firm profits. We obtain the result that heat shocks have no significant effect on profit shocks. We are unfortunately unable to observe the exact mechanisms between weather and firm profits, including any adaptive practices such as increased marketing or product adjustments. Therefore, the null effect between weather extremes and dairy processors' profits estimated here, might be caused either by excellent management of these risks or by heat extremes having no economic impact on dairy processors' profits. If data becomes available future research should study these mechanisms more closely to analyze management behaviors of dairy firms during climatic shocks.

6 Conclusion

This study applies fixed effects panel regression to estimate the impact of temperature humidity shocks on the profits of dairy processing firms in Europe. The data is obtained from 1’403 dairy processing firms over 9 years (2011-2019) resulting in 12’473 observations in total. Based on various robustness checks using different proxies for profits (turnover and return on equity), different proxies for heat (using different extreme temperature and humidity thresholds), spatial sub-samples, and sub samples by firm size we consistently show that local heat extremes have no significant impact on the performance of dairy processors in Europe, which is in contrast to our hypothesis. We discuss that risks of heat extremes in the dairy system are mainly borne by farms rather than processors.

For policy makers our results imply that supporting efforts to cope with climatic extremes should focus on the dairy farm level rather than the dairy processing industry. Market mechanisms seem to not allow shifting losses from the farm level along the value chain to the processing industry. In case of an increasing heat exposure under climate change, it is crucial for farmers to develop efficient and effective farm level risk management strategies.

Although our reduced form model shows that heat extremes do not affect dairy processors’ profits, we are unable to observe if there are any management mechanisms between weather extremes and firm profits, such as adjustments in marketing or the composition of processed products. Therefore, future research should more closely look at how managerial practices of dairy processors are affect by climatic shocks to better understand how to cope with weather extremes.

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Appendix

Appendix A: Full Regression results for main specification and different THI thresholds

Table A.1 Regression output on log(turnover) based on the $THI_{threshold}$ value of 75

Log(Turnover)	**Estimate**	**t-value**	**p-value**
THI_75 [days]	9e-05 (0.0007)	0.13	0.89

Note: In the brackets are standard errors clustered by firm and year; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Fixed effects	Firm and year
Number of observations	12,473
RMSE	0.4196
Adjusted R^2	0.95
Within R^2	0.00

Table A.2 Regression output on log(turnover) based on the $THI_{threshold}$ value of 80

Log(Turnover)	**Estimate**	**t-value**	**p-value**
THI_80 [days]	-5e-04 (0.0007)	-0.71	0.50

Note: In the brackets are standard errors clustered by firm and year; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Fixed effects	Firm and year
Number of observations	12,473
RMSE	0.4196
Adjusted R^2	0.95
Within R^2	0.00

Table A.3 Regression output on log(turnover) based on the $THI_{threshold}$ value of 85

Log(Turnover)	**Estimate**	**t-value**	**p-value**
THI_85 [days]	-1.5e-03 (0.0009)	-1.65	0.14

Note: In the brackets are standard errors clustered by firm and year; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Fixed effects	Firm and year
Number of observations	12,473
RMSE	0.4195
Adjusted R^2	0.95
Within R^2	0.00

Table A.4 Regression output on ROE based on the $THI_{threshold}$ value of 75

ROE	**Estimate**	**t-value**	**p-value**
THI_75 [days]	0.047 (0.046)	1.03	0.33

Note: In the brackets are standard errors clustered by firm and year; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Fixed effects	Firm and year
Number of observations	12,056
RMSE	41.2
Adjusted R^2	0.21
Within R^2	0.00

Table A.5 Regression output on ROE based on the $THI_{threshold}$ value of 80

ROE	**Estimate**	**t-value**	**p-value**
THI_80 [days]	0.049 (0.044)	1.11	0.30

Note: In the brackets are standard errors clustered by firm and year; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Fixed effects	Firm and year
Number of observations	12,056
RMSE	41.2
Adjusted R^2	0.21
Within R^2	0.00

Table A.6 Regression output on ROE based on the $THI_{threshold}$ value of 85

ROE	**Estimate**	**t-value**	**p-value**
THI_85 [days]	0.045 (0.075)	0.60	0.56

Note: In the brackets are standard errors clustered by firm and year; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Fixed effects	Firm and year
Number of observations	12,056
RMSE	41.2
Adjusted R^2	0.21
Within R^2	0.00

Appendix B: Full regression results for spatial sub-samples

We split all the dairy processing firms into four spatial regions. Northern Europe consists of firms with latitude above 44.5 N, and southern Europe consists of firms with latitude below 44.5 N. Eastern Europe consists of firms with longitude above 10.3 E, and western Europe consists of firms with a longitude below 10.3 E.

Table B.1 Regression output on log(turnover) based on the $THI_{threshold}$ value of 75

Log(Turnover)	**Eastern firms**		**Western firms**		**Northern firms**		**Southern firms**	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	-8.6e-04 (0.0012)	0.50	9.8e-04 (0.0005)	0.11	4.5e-04 (0.001)	0.62	-1.6e-04 (0.0006)	0.78
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	6’214		6’259		6’495		5’978	
RMSE	0.50		0.32		0.46		0.37	
Adjusted R^2	0.92		0.98		0.95		0.95	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Table B.2 Regression output on log(Turnover) based on the $THI_{threshold}$ value of 80

Log(Turnover)	**Eastern firms**		**Western firms**		**Northern firms**		**Southern firms**	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	-2.4e-03 (0.0012)	0.09	1.8e-03 * (0.0007)	0.03	4.4e-05 (0.001)	0.97	4.0e-04 (0.0008)	0.63
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	6'214		6'259		6'495		5'978	
RMSE	0.50		0.32		0.46		0.37	
Adjusted R^2	0.92		0.98		0.95		0.95	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Table B.3 Regression output on log(Turnover) based on the $THI_{threshold}$ value of 85

Log(Turnover)	**Eastern firms**		**Western firms**		**Northern firms**		**Southern firms**	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	-4.7e-03* (0.0019)	0.04	1.8e-03 (0.0012)	0.17	1.3e-03 (0.0015)	0.43	7.7e-04 (0.0009)	0.46
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	6'214		6'259		6'495		5'978	
RMSE	0.50		0.32		0.46		0.37	
Adjusted R^2	0.92		0.98		0.95		0.95	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Table B.4 Regression output on ROE based on the $THI_{threshold}$ value of 75

ROE	Eastern firms		Western firms		Northern firms		Southern firms	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	0.014 (0.036)	0.72	0.06 (0.09)	0.50	-0.030 (0.072)	0.69	0.098 (0.063)	0.16
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	6’024		6’032		6’278		5’778	
RMSE	43.4		38.9		40.7		41.7	
Adjusted R^2	0.21		0.21		0.23		0.18	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Table B.5 Regression output on ROE based on the $THI_{threshold}$ value of 80

ROE	Eastern firms		Western firms		Northern firms		Southern firms	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	0.05201 (0.0599)	0.41	0.007 (0.049)	0.89	0.054 (0.092)	0.57	0.058 (0.045)	0.24
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	6’024		6’032		6’278		5’778	
RMSE	43.4		38.9		40.7		41.7	
Adjusted R^2	0.21		0.21		0.23		0.18	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Table B.6 Regression output on ROE based on the $THI_{threshold}$ value of 85

ROE	**Eastern firms**		**Western firms**		**Northern firms**		**Southern firms**	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	0.033 (0.117)	0.79	0.026 (0.073)	0.73	-0.037 (0.14)	0.79	0.115 (0.08)	0.19
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	6’024		6’032		6’278		5’778	
RMSE	43.4		38.9		40.7		41.7	
Adjusted R^2	0.21		0.21		0.23		0.18	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Appendix C: Regression results for company sizes sub samples

Table C.1 Regression output on log(turnover) based on the $THI_{threshold}$ value of 75

Log(Turnover)	**Micro firms**		**Small firms**		**Medium firms**		**Large firms**	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	-2.25e-04 (8.84e-04)	0.81	-6.64e-04 (7.91e-04)	0.43	-7.95e-04 (1.17e-03)	0.52	-9.8e-04 (2.28e-03)	0.68
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	4’130		4’467		2’007		569	
RMSE	0.41		0.38		0.32		0.30	
Adjusted R^2	0.95		0.91		0.94		0.94	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Table C.2 Regression output on log(turnover) based on the $THI_{threshold}$ value of 80

Log(Turnover)	**Micro firms**		**Small firms**		**Medium firms**		**Large firms**	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	-7.95e-04 (9.19e-04)	0.41	-8.15e-04 (8.74e-04)	0.38	-1.17e-03 (1.08e-03)	0.31	1.03e-03 (2.89e-03)	0.73
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	4’130		4’467		2’007		569	
RMSE	0.41		0.38		0.32		0.30	
Adjusted R^2	0.95		0.91		0.94		0.94	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Table C.3 Regression output on log(turnover) based on the $THI_{threshold}$ value of 85

Log(Turnover)	**Micro firms**		**Small firms**		**Medium firms**		**Large firms**	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	-1.59e-03 (1.21e-03)	0.23	-2.58e-03 (1.18e-03)	0.06	-8.75e-04 (1.43e-03)	0.56	3.00e-03 (3.90e-03)	0.46
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	4’130		4’467		2’007		569	
RMSE	0.41		0.38		0.32		0.30	
Adjusted R^2	0.95		0.91		0.94		0.94	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Table C.4 Regression output on ROE based on the $THI_{threshold}$ value of 75

ROE	Micro firms		Small firms		Medium firms		Large firms	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	0.12 (0.11)	0.30	0.02 (0.03)	0.52	-0.15 (0.13)	0.29	-0.05 (0.04)	0.29
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	3’870		4’372		1’904		556	
RMSE	51.6		30.3		45.2		27.9	
Adjusted R^2	0.19		0.27		0.19		0.23	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Table C.5 Regression output on ROE based on the $THI_{threshold}$ value of 80

ROE	Micro firms		Small firms		Medium firms		Large firms	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	0.13 (0.09)	0.20	-0.013 (0.04)	0.73	-0.14 (0.14)	0.37	0.05 (0.10)	0.63
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	3’870		4’372		1’904		556	
RMSE	51.6		30.3		45.2		27.9	
Adjusted R^2	0.19		0.27		0.19		0.23	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.

Table C.6 Regression output on ROE based on the $THI_{threshold}$ value of 85

ROE	**Micro firms**		**Small firms**		**Medium firms**		**Large firms**	
	Estimate	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**	**Estimate**	**p-value**
Heat extremes	0.20 (0.11)	0.09	-0.05 (0.11)	0.69	-0.18 (0.32)	0.60	-0.36 (0.39)	0.39
Fixed effects	Firm and year		Firm and year		Firm and year		Firm and year	
Number of observations	3'870		4'372		1'904		556	
RMSE	51.6		30.3		45.2		27.9	
Adjusted R^2	0.19		0.27		0.19		0.23	
Within R^2	0.00		0.00		0.00		0.00	

Note: In the brackets are standard errors; *, **, *** indicate significant levels at 5 %, 1 %, and 0.1 %respectively.