The Distributional Aspects of Climate Change’s Impact on Swedish Dairy Farm Productivity

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Distributionella aspekter av klimatförändringarnas effekter på svenska mjölkgårdars produktivitet

Ella Li Jennersjö

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Abstract

This study investigates the relationship between dairy farm productivity and high temperatures in Sweden over the period 2002–2021, addressing a significant research gap related to both geographical location and production method within the literature on climate change's impact on agricultural production.

Using a Recentered Influence Function method combined with Unconditional Quantile Regression, we estimate the effect of an additional day per year with temperatures exceeding 25°C on various productivity quantiles. This approach captures not only the effect of extreme temperature days but also how the impact varies across the productivity distribution.

The results reveal stronger effects for lower-productivity farms as well as for organic farms. However, for organic farms, the effect is less statistically significant, suggesting considerable heterogeneity within this subgroup. These findings are then interpreted in the context of previous research, mainly conducted outside Northern Europe, that links high temperatures to productivity losses through three main channels: loss in cow health and fertility, reduced pasture quality, and decreased milk yield. Contrary to expectations, this study finds an increase in milk yield, potentially attributed to higher purchases of concentrate feed, which likely compensate for diminished pasture quality. No evidence supporting claims of high temperatures negatively impacting cow health was identified.

The results contribute to the literature by enhancing our understanding of the distributional impacts of climate change on farm productivity. They may offer valuable insights for future policy development, as well as for farmers and extension workers who will face the challenges posed by climate change firsthand.

Keywords: Climate change, Dairy production, RIF-Regression, Distributional effects

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List of Abbreviations

FADN	Farm Accountancy Data Network.
IF	Influence Function.
JOU	The Farm Economics Survey.
LU	Livestock Unit.
RIF	Recentered Influence Regression.
SMHI	The Swedish Meteorological and Hydrological Institute.
TFP	Total Factor Productivity.
UQR	Unconditional Quantile Regression.

1. Introduction

Multiple studies have looked at the interaction between climate change and farm productivity, consistently finding a negative relationship between increases in temperature, seasonal variability and precipitation patterns and farm productivity (Amare and Balana 2023; Harrison, Cullen, and Armstrong 2017; Hughes et al. 2022). However, most of these studies focus on the effects of climate change in already climatically challenged regions, and on the effects of climate change on crop farming specifically (Martinsohn and Hansen 2012). This has created a significant research gap regarding the effects of climate change on other regions and production methods, for example animal production systems in Northern Europe.

While the research gap might suggest a low relevance for further study, recent developments have indicated an interest to study the impact of climate change on Northern European farms as well. Notably, the recent Swedish drought in 2018, which saw both extensive periods of above normal temperature, as well as a decrease in groundwater and streamflow water (Bakke, Ionita, and Tallaksen 2020; Rakovec et al. 2022), highlights the relevance of this issue. In response to the drought, the Swedish government introduced temporary support for animal farms and reduced slaughterhouse fees, while making few adjustments for crop farms (The Swedish Government Offices 2018). The exclusive focus on animal farms in the support program signals the specific relevance of this study: the distribu- tional effects of increasing temperatures on dairy farm productivity. Despite the assumed large-scale consequences of the 2018 drought (Swedish Board of Agriculture 2019), long-term studies of the impacts remain scarce, leaving our understanding of climate change's impact on farm productivity underdeveloped.

While the drought of 2018 seems to have had greater impact on animal than on crop farms, previous studies show indications of heterogeneous effects following extreme weather events spanning a wide array of characteristics, such as between conventional and organic agricultural production as well as between geographical localization and farm size (Moghaddam et al. 2024; Wimmer, Stetter, and Finger 2023; Wittwer et al. 2023). Understanding the distribution of these effects is critical both for our understanding of potential consequences of climate change (Rakovec et al. 2022), as well as for the construction of efficient related policy (Unc et al. 2021).

Based on the issue outlined above, with indications of climate change impacting Swedish animal farms to a larger yet unknown extent than crop farms, this thesis seeks to address the research gaps by studying the impact of climate change on Swedish animal farms, focusing on the distributional effects of this issue. To delimit our study further, in order to provide a more clear interpretation of results, we look especially at dairy farms. Dairy farms were among the farms especially vised by policy post drought in 2018, and hold both a strong cultural value in Sweden (Martiin 2010), and receive large amounts of national and EU-based subsidies (McCloud and Kumbhakar 2008). Delimiting our studied sample to Swedish dairy farms is thus motivated both from an economic and social point of view.

To perform a detailed analysis of the effects of climate change on dairy production, this paper employs a Recentered Influence Function (RIF) method, using Unconditional quantile Regression (UQR) as proposed by Firpo, Fortin, and Lemieux (2009). This allows a nuanced study of the distributional effects of climate change in large detail across a sample of Swedish dairy farms, in regards to both total factor productivity and production method. We study the effect of extreme temperature on farm total factor productivity across the full sample, as well within subgroups of organic and conventional farms, and identify key contributing factors behind our results.

Our findings show that farm productivity is significantly negatively impacted by daily average temperatures above 25 degrees, mainly due to increases in feed purchase. The losses to productivity is partially offset by increased milk production, connected to the changes in feed consumption. However, this increase in production does not outweigh the cost associated with the increases in feed purchased. Furthermore, results differ between organic and conventional farms: conventional farms display a more homogeneous effect across quantiles, while the impact on organic farms is larger albeit less significant.

This thesis contributes to the literature on climate change and agricultural productivity in four main ways. First, it is the first study to apply a RIF method to analyze the distributional impact of extreme temperatures on farm productivity, providing a new depth to our understanding of how farm characteristics may affect climate change impact. Secondly, by combining detailed farm-level data from the Farm Accountancy Data Network (FADN) with municipal weather data from the Swedish Meteorological and Hydrological Institute (SMHI), the study provides novel empirical evidence on how daily average temperatures above 25°C disproportionately affect lower-performing Swedish farms. Third, the analysis identifies the main mechanism behind productivity losses to be an increase in purchased feed costs, while also showing that milk yield and veterinary expenses play a lesser role. As this rules our impact factors identified in previous studies, this is an important policy contribution. Finally, the study compares organic and conventional farms, revealing greater variability in responses among organic farms, emphasizing the need for well adapted climate policies. These contributions fill a key gap in Northern European climate impact research and have clear policy implications for the resilience of dairy farming systems.

The remainder of this study will proceed as follows: Section 2, will present the theoretical background, foundational for the subsequent analysis. Section 3 present the data, followed by Section 4 developing on the method employed in this study. Section 5 presents the results, and the study concludes with Section 6 presenting the conclusions and policy implications derived from this.

2. Background

2.1 The impact of climate change on dairy production

Within a Northern European context, literature on the matter of climate change and dairy farm production is notably scarce, possibly as the effects of climate change are not yet as visible in these regions as compared to many others (Martinsohn and Hansen 2012). Numerous studies point to these regions gaining added production possibilities with climate change (Moore and Lobell 2014; Wiréhn 2018). However, this is all dependent on the region's ability to adapt to the changes, both in terms of policy (Unc et al. 2021; Wiréhn 2018) as well as in regards to changes in temperatures and precipitation patterns causing, for example, a higher need for irrigated farming systems (Grusson, Wesström, and Joel 2021).

Previous studies, mainly focusing on the impact of temperature on dairy production in already climatically challenged regions, is however plenty. One of the main factors impacting dairy production with increased heat is a loss to milk yield per cow. Discussed in both Nardone et al. (2010) and Wankar and Rindhe (2021), the milk yield of a dairy cow is negatively impacted by heat stress, with higher yielding cows deemed more susceptible to heat stress than lower yielding cows. Controlled experiments show milk yield being reduced by as much as 35% when the cow was subject to extended periods of heat stress. The impact of heat stress on dairy cattle has been studied within a Swedish context, by Ahmed, Tamminen, and Emanuelson (2022), showing that Swedish dairy cattle show signs of being negatively impacted by heat stress already at 22°C.

Increasing temperatures have also been connected to a increase in veterinary costs in dairy farming, posing potential consequences for farm factor productivity. Heat has been shown to decrease fertility among cattle (Hughes et al. 2022; Wankar and Rindhe 2021), decreasing profit due to lower herd size and higher breeding costs. Guzmán-Luna et al. (2022) also note that increasing temperatures cause a higher dispersion and growth rate of many pathogens, increasing the risk of disease in dairy cattle, both potentially causing higher veterinary cost as well as lowered milk yield due to ill health.

Harrison, Cullen, and Armstrong (2017) also connects climate change, with increasing temperature and lowered precipitation, to profit losses from lesser pastures. Arguing that this causes farmers to buy more added feed to sustain production. The Australian context of this study causes concern for its' external validity, and relevance to the Swedish context of this thesis, however. Many studies point at opposing effects of increasing temperatures within northern European pasture production, an increase in pasture growth with climate change (Höglind, Thorsen, and Semenov 2013). However, an increased pasture growing rate may cause lower protein contents per kg of ley, lowering nutritional values of the pasture, causing the necessity of added feed (Dellar et al. 2018) .

To conclude, previous literature identifies three primary pathways through which elevated temperatures may negatively affect the productivity of Swedish dairy farms: reduced milk yield, pasture growth, and animal health. Building on our main findings, suggesting a potential negative association between high temperatures and productivity, section 5.2, “The Mechanisms”, explores how these factors contribute to the observed productivity losses in Swedish dairy farming.

2.2 The distributional effects of climate change

Previous literature have shown differentiated effects of climate change based on different farm characteristics (Wimmer, Stetter, and Finger 2023; Wittwer et al. 2023; Moghaddam et al. 2024). Wittwer et al. (2023) study on crop yields, concludes that there is little differences on the drought resistance between organic and conventional farming systems. These results have been contradicted by Moghaddam et al. (2024) who, performing a metastudy of 44 drought studies, find results showing that organic farms generally are less economically impacted by drought than their conventional counterparts. Results from Moghaddam et al. (2024) are generally attributed to lesser costs of input in organic farming, which tend to be more circular systems than conventional farms. As stated however, literature has not found unity on the interaction between production method and impact from climate change, which is something that will be studied in this thesis.

The distributional effects of climate change on productivity distributions have been studied most notably by Malikov, Miao, and Zhang (2020) and Zhang, Malikov, and Miao (2024). Both studies conclude that there are significant distributional effects associated with the impact of climate change on productivity, both within the agricultural sector, and outside it. This implies that in order to understand the impacts of climate change on Swedish dairy farms, it is also important to study the associated distributional effects, otherwise, we risk losing an important perspective of the issue at hand, reducing our understanding of the situation.

3. Data

The main data used in this model comes from the Farm Accountancy Data Network (FADN), from Eurostat. The FADN provides detailed information on farm level economic transactions, as well as basic farm characteristics. The Swedish sample of FADN consist of The Farm Economics Survey (Swedish: Jordbruksekonomiska Undersökningen, or JOU), a questionnnaire for which *at least* 1025 farms are selected randomly yearly. As FADN includes all kinds of farms, we delimited our sample to Swedish farms whose main income comes from dairy production. This resulted in an unbalanced dataset of a total of 6552 observations on 759 farms, spanning the years of 2002-2023.

Climate data was provided by the Swedish Meteorological and Hydrological Institute (SMHI). For this thesis, we used daily average temperature on municipality level, over the years 2002-2023. All municipalities are present for all years studied, making it a perfectly balanced panel. One key limitation of this study lies in the spatial resolution of the weather data. While FADN provides farm-level data, the corresponding temperature data is available only at the municipality level. This introduces potential measurement errors if within-municipality climate heterogeneity exists, which is particularly likely in larger municipalities. This is a well-known issue when studying temperature impact on local level (see Zhang, Malikov, and Miao 2024; Ahmed, Tamminen, and Emanuelson 2022), and as such we have modeled our approach to be consistent with related empirical literature. Given that most Swedish municipalities are relatively small and climatologically homogeneous however, we consider municipal level data a reasonable option, which still allows us to identify meaningful variation in exposure to extreme temperature events.

3.1 Variables

The main dependent variable in this thesis is Total Factor Productivity, TFP. Following previous literature (eg Karafillis and Papanagiotou (2011) and Coomes et al. (2019)), TFP is defined as the ratio of aggregate output (q) by aggregate input (x), such that:

$$TFP = \frac{Q(q)}{X(x)} \tag{1}$$

All variables used in this thesis are logarithmized for interpretability, except Temperature, and when appropriate they are also weighted by number of Livestock Unit (LU) reported at farm level. Table 1 present a comprehensive list of the variables used.

Table 1. Variable List

Variable name	Description	Source
TFP	Farm Total Factor Productivity	FADN
Vet costs	Veterinary costs in SEK per year, weighted by LU	FADN
Milk yield	Milk yield per cow, in KG	FADN
Home feed	Feed produced at farm in tonnes, weighted by LU	FADN
Purchased conc	Concentrates purchase in SEK, weighted by LU	FADN
Net income	Farm net income in SEK weighted by LU	FADN
Value added	Farm net value added weighted by LU	FADN
Temperature	Average daily temperature per municipality in ^{o}C	SMHI

3.2 Summary statistics

Summary statistics are presented in Table 3.

Table 2. Summary Statistics

Variable name	Obs	Mean	Std. Dev	Min	Max
TFP	6522	0.94	0.194	0.188	1.88
Net income	6522	46718	91702	-1197521	1486270
Purchase conc	6522	702628	1199819	0	18700000
Milk yield	6522	7686	2865	0	109000
Home feed	6522	67082	86031	0	1257448
Vet costs	6522	38980	673015	0	1191670
Value added	6522	106058	167860	-2211991	2606085
Temperature	10115	6.2956	2.33	-41	26.9

The extremely high maximum values observed for the variables Vet cost and Purchase conc suggest that some observations may represent aggregated entities, such as companies comprising multiple production units, rather than single farms. To address this, we divided all variables by LU to normalize for scale and studied the residual plots to assess model fit. Subsequently, all previously extreme observations fell within a reasonable range, and no influential outliers remained. As a result, all observations were retained in the sample.

3.3 Temporal trends

The temporal trend of monthly average temperatures within the studied time period is illustrated below in Figure 1. Average temperature has been consistently increasing over the studied time period. This motivates the study of the impact of increasing temperatures on farm TFP.

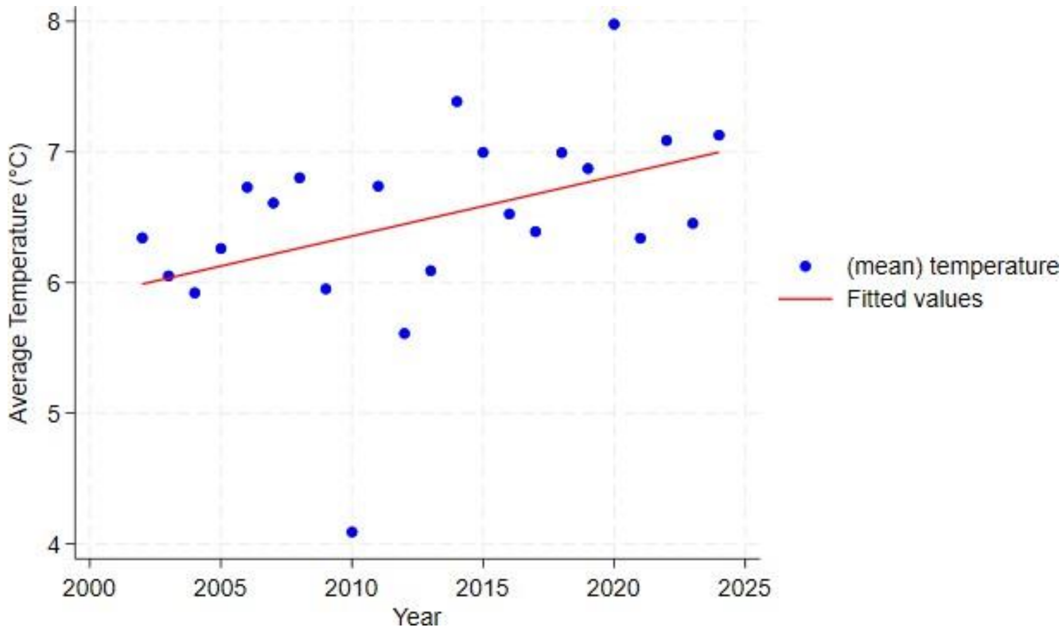

Figure 1: Development of yearly average temperature in Sweden 2002-2022

3.4 Temperature Bin Construction

Following Zhang, Malikov, and Miao (2024), we study the effect of temperature on our dependent variable is measured using temperature bins. Temperature bins have been widely used in literature, such as by Ahmed, Tamminen, and Emanuelson (2022), Ortiz-Bobea et al. (2025), and Zhang, Malikov, and Miao (2024), and are advantageous to use as it provides easily interpretable coefficients, that is also able to capture nonlinearities in temporal effects, making it able to display complexities despite its simple structure.

We collect data on average daily temperature (T_d) in municipality i, partitioned into eight bins ($\mathbf{B}_i$) in increments of five degrees, following the bin structure of Ahmed, Tamminen, and Emanuelson (2022). These bins are aggregated to the annual level t, resulting in a measure of the number of days per year and municipality with an average temperature falling within each bin range. The bins are defined as $T_d \leq -5^{\circ}\mathrm{C}$, $T_d \in [-5^{\circ}\mathrm{C}, 0^{\circ}\mathrm{C})$, ..., $T_d \in [20^{\circ}\mathrm{C}, 25^{\circ}\mathrm{C})$, and $T_d \geq 25^{\circ}\mathrm{C}$.

The final bin [$T_d \geq 25^{\circ}\mathrm{C}$] serves as a natural upper threshold, as such high average daily temperatures are rare in Sweden. An earlier specification also included a bin for $T_d > 30^{\circ}\mathrm{C}$, but since no observations fell into this category, it was omitted from the final construction.

The final bin construction and its distribution is presented in the table below.

Table 3. Temperature Bin Distribution

Temperature Bin (˚C)	Mean	Std. Dev	Min	Max
≤-5	24.37	25.02	0	137
-5 to 0	48.28	19.30	0	127
0 to 5	83.32	17.74	38	132
5 to 10	68.81	16.42	21	121
10 to 15	73.82	14.80	33	114
15 to 20	56.70	18.10	0	104
20 to 25	9.80	8.96	0	45
≥25	0.11	0.50	0	6

Visibly, all temperature bins are present somewhere in the sample, with the most extreme bins [≤-5˚C] and [≥25˚C] being the least represented bins.

4. Method

To study the distributional effects of rising temperatures on Swedish dairy farm productivity, we estimate a Recentered Influence Function (RIF) using Unconditional Quantile Regression (UQR) (Firpo, Fortin, and Lemieux 2009). The RIF method, combined with UQR is a widely used method when studying distributional aspects of policy and/or temperature, providing easily yet detailed information across the studied sample (Firpo, Fortin, and Lemieux 2018; Clementi and Fabiani 2024; Zhang, Malikov, and Miao 2024).

The RIF-method is especially advantageous in this setting as it allows us to recenter our focal point around specific quantiles of the distribution of the dependent variable. This is in contrast to an ordinary OLS regression, where we would get a full sample mean, lacking the detailed understanding of how climate change may impact farm productivity. As previous studies imply heterogeneous effects from increasing temperatures, the detailed analysis we get from the RIF-regressions is thereby suitable to study the issue at hand. The RIF method is further combined with an UQR, suitable for this purpose as it is conditional only on the outcome variable, not tied to specific levels of the independent variable - making it easily interpretable and usable from a policy perspective.

The RIF-regression method is centered around the idea of studying how a specific quantile, q_τ, of a large sample is impacted by a small change in x. Or in mathematical terms:

$$\frac{\partial q_\tau}{\partial x} \tag{2}$$

We begin by estimating a simple Influence Function (IF) as follows:

$$IF(Y_{it}, q_\tau) = \frac{\tau - \mathbf{1}\{Y_{it} \leq q_\tau\}}{f_Y(q_\tau)} \tag{3}$$

Where Y_{it} is the dependent variable, q_τ the studied quantile and the term $\mathbf{1}\{Y_{it} \leq q_\tau\}$ a binary function given the value one in case the observation is found at, or below, the studied quantile.

The denominator $f_Y(q_\tau)$ is the density of the distribution of the dependent variable Y_{it} at quantile q_τ. To estimate this density, this thesis employs a Gaussian kernel density estimation, a nonparametric technique that smooths the distribution locally around the quantile of interest, as proposed by Firpo, Fortin, and Lemieux (2009). This estimate is critical because it scales the influence function, reflecting how observations near the quantile impact the RIF regression. Accurate estimation of $f_Y(q_\tau)$ enhances the reliability and interpretability of the marginal effects obtained through the RIF regressions.

From this follows that a value of Y_{it} found below the quantile, the IF will be positive, and vice versa. However, this produces a situation where the IF will inevitably have a mean of zero, as per:

$$\mathbb{E}[IF(Y; q_\tau)] = 0 \tag{4}$$

This leads us to our final step, the re-centering of the influence function, the RIF. The baseline RIF-regression model looks as follows:

$$RIF(Y_{it}, q_\tau) = q_\tau + \frac{\tau - \mathbf{1}\{Y_{it} \leq q_\tau\}}{f_Y(q_\tau)} \tag{5}$$

Which carries the influence function from equation 2, and adds the quantile studied, q_τ. This re-centers the IF such that instead of having a natural mean of zero we get the expected value as:

$$\mathbb{E}[IF(Y; q_\tau)] = q_\tau \tag{6}$$

Which means that the IF is now centered around the quantile studied, meaning that when running a regression on the RIF, the interpretation of the coefficient will be as the marginal effect of a small change in the covariates for the defined quantile of the sample.

To this regression we add as control variables our temperature bins as described in section 3.4 The specified regression will look as follows:

$$RIF(Y_{it}, q_\tau) = \sum_{j=1}^{7} \beta_j \boldsymbol{B}_{it}^{(j)} + \omega_{it} + \varepsilon_{it} \tag{7}$$

With Y_{it} being the dependent variable, for farm i in year t, weighted by LSU to adjust for size-effects, and $\boldsymbol{B}_{it}^{(j)}$ a vector for the temperature bins, of which the middle one [10-15°C] was omitted from all regressions as a benchmark temperature. q_τ is the studied unconditional quantile of our dependent variable. β is our coefficient measuring the effect of an increased amount of day within the temperature range of bin j. ω_i is farm fixed-effects and ε is our error term with all its usual properties. All regressions employ farm-level clustered standard errors, accounting for correlation of the error terms within farms over time. This adjustment is standard practice in panel data settings to avoid underestimating standard errors due to within-farm dependence.

Finally, this RIF regression will be estimated for all variables present in the variable list, with the exception of *Temperature*, which serves as baseline for our key explanatory variable in all regressions. Our main results stem from the RIF regression using TFP as dependent variables, while the other variables either investigate the mechanisms working behind the temperature impact to TFP, or act as robustness checks. Each RIF regression is estimated across 10 unconditional quantiles, representing the 10th through 90th quantiles in 10-degree increments, such that $q_\tau \in [10, 20, ..., 90]$.

5. Empirical Results

5.1 Main Results

To study the distributional effects of temperature on Swedish dairy farm TFP, we perform a number of RIF-regressions, using unconditional quantile regressions. First, we regress temperature on farm TFP, to identify any possible effects of temperature on our dependent variable. Thereon, we study the cause of our findings in our primary regression, by estimating a number of further regressions. Finally, a set of three robustness checks are be found under section 5.2.3.

For interpretability, the result section will be presented in the form of graphs, showing both an average trend and a color-coded analysis for each studied quantile.

We begin by estimating the effect of temperature on logarithmic TFP, in order to study the distribution of the effect of temperature on farm TFP. This will subsequently be referred to as our main results. We omit bin 5 [10-15°C], making it our reference temperature. The interpretation of coefficients is thus given as the impact to farm TFP following *one added day* of temperature deviating from our reference temperature. Bin 5 was chosen as a reference temperature as it is the most well represented bin in our sample, providing a natural baseline for analysis.

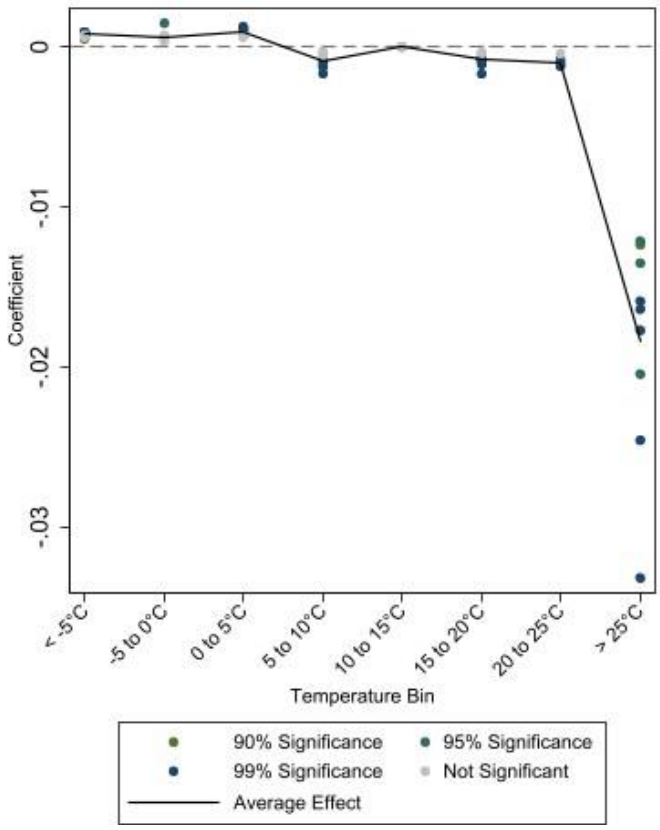

Figure 2: Average and quantile temperature effects to TFP

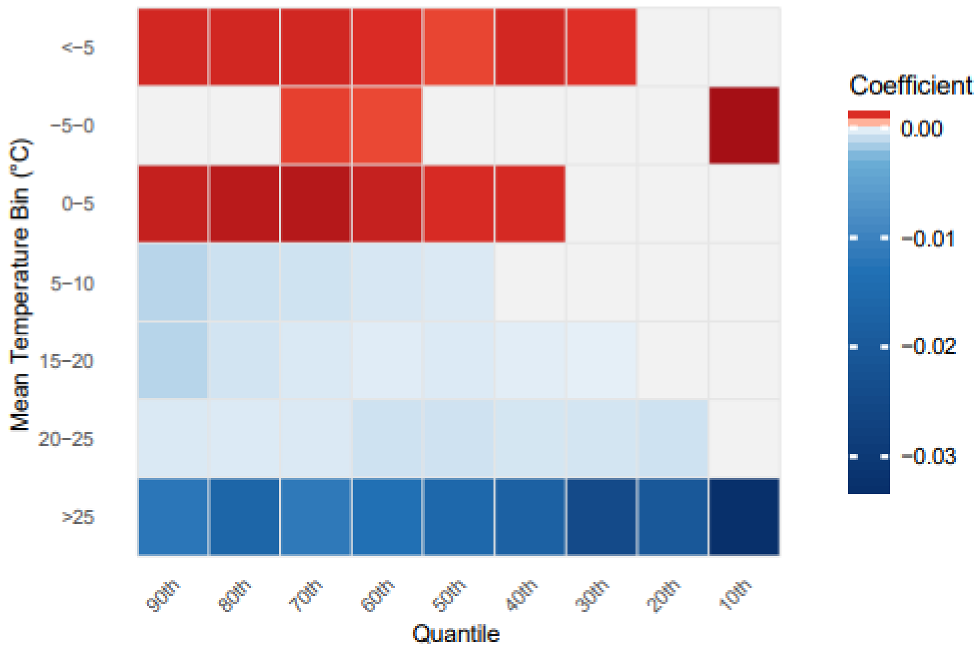

Figure 3: Matrix summation of coefficients

Circle bubbles in Figure 2 correspond to a coefficient estimate from the RIF regression of temperature bins on logarithmic and weighted TFP. Each bubble signifies the impact to TFP of *one added day* deviating from benchmark temperature [10-15˚C], per TFP quantile. Blue bubbles are significant to 99%, mauve to 95% and green bubbles to 90%. Grey bubbles display insignificant results. The solid black line follows the mean estimate of all coefficients. Extensive result tables from all discussed RIF-regressions will be found in appendix A, selected coefficients from these regressions are discussed below.

Results in Figure 2 show a large and statistically significant loss in TFP for all quantiles studied, associated with one added day of mean temperature ≥25˚C. This follows previous literature, stating that elevated temperatures cause negative impacts to cow health and fertility, feed production and milk yield, all of which would impact farm TFP negatively. This effect is statistically significant across all quantiles, but with the 90th, 80th and 70th quantiles all being significant at only 90%, and with lower magnitude to their coefficients than in the lower part of the distribution. For reference, one added day of temperatures
≥25˚C would incur a loss to TFP of 0.012% for the upper 90th quantile, but for the 10th quantile, this loss would be three times larger, at 0.033%. This implies that low productivity farms face larger impacts from one added day with an average temperature above 25 ˚C, than farms with high productivity levels. This distributional heterogeneity is in line with previous studies, stating that high productivity is a factor increasing resilience in view of increasing temperatures (Moghaddam et al. 2024; Zhang, Malikov, and Miao 2024)

Figure 3 plots a matrix of all coefficients presented in Figure 2, visualizing the magnitude of temperature effects on each production quantile. All coefficients significant to at least the 90% level are represented by a color, blue if the coefficient is negative and red if it is positive, increasingly dark as the coefficient increases. Visibly, farms within the upper range of the productivity distribution see effects from almost all temperatures deviating from our baseline temperature [10-15˚C], however, the effect is notably stronger (visualized by a darker color) towards the lower ends of the quantile spectrum, implying that these farms are the most affected by extreme temperatures.

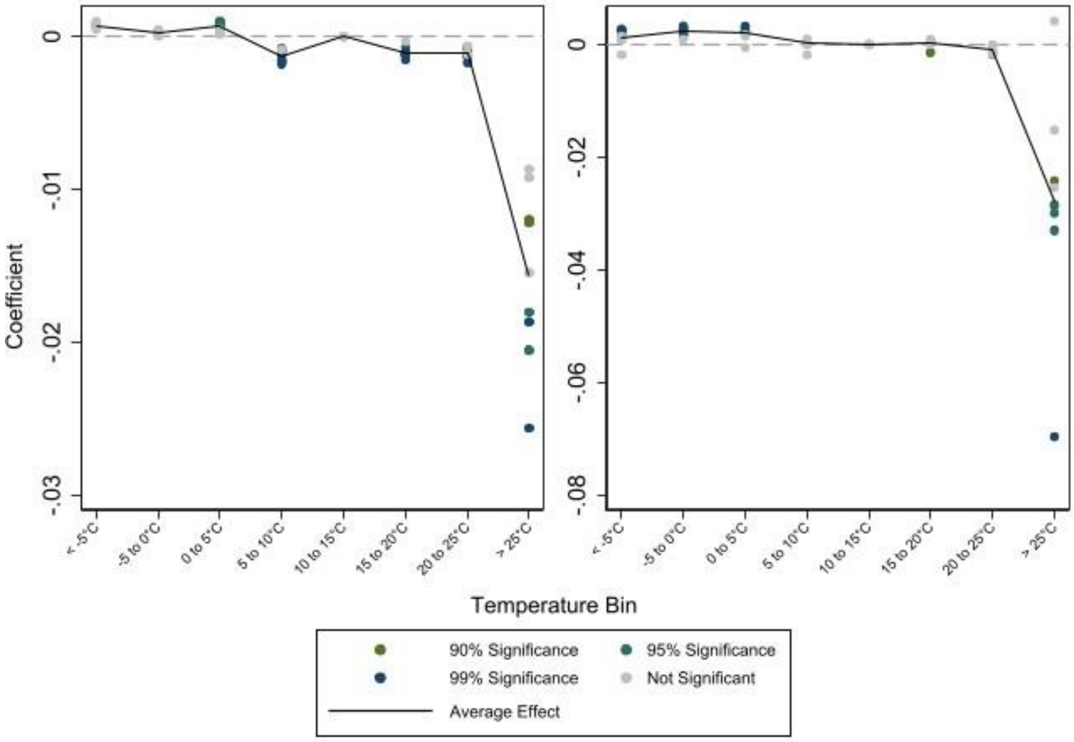

Figure 4: Average and quantile effects to TFP for the subsamples conventional and organic farms.

Note: on the left hand side, the analysis is performed for the subsample conventional farms, on the right hand side, the subsample is organic farms

Figure 4 displays the analysis from Figure 2 reproduced, but with the subsamples of conventional farms (left panel), and organic farms (right panel). The findings for the organic farm present much higher coefficients than the conventional farms. This suggests that increases in temperature have a larger impact on productivity for organic farms than conventional farms.

For the estimation concerning organic farms, it is mainly observations in the middle lower ends of the productivity distribution that create significant coefficients. This implies that organic farms with lower TFP might be able to sustain increasing temperatures with smaller losses to TFP than other studied quantiles. This is developed upon in Le Gal et al. (2011) suggesting that small-scale, diversified farms, while less productive, often are more flexible and adaptive than large-scale, specialized farms. Organic farms are stated to be more diversified by construction, and report five lesser LU on average per farm in the studied sample. This could be a possible explanation to the lower productivity organic farms sustaining extreme temperatures better than high productivity ones, but more research is needed on this matter.

5.2 The mechanisms

The results in figures 2-4 confirms the idea that climate change negatively impact TFP of Swedish dairy farms. It tells us very little of the mechanisms behind this however. Following previous studies, developed upon in the background of this thesis, this section will develop upon the possible mechanisms impacting the dairy farm TFP during high temperatures.

Following Ahmed, Tamminen, and Emanuelson (2022), finding negative effects to milk yields at above average temperatures, we estimate the effect of our temperature bins on milk yield.

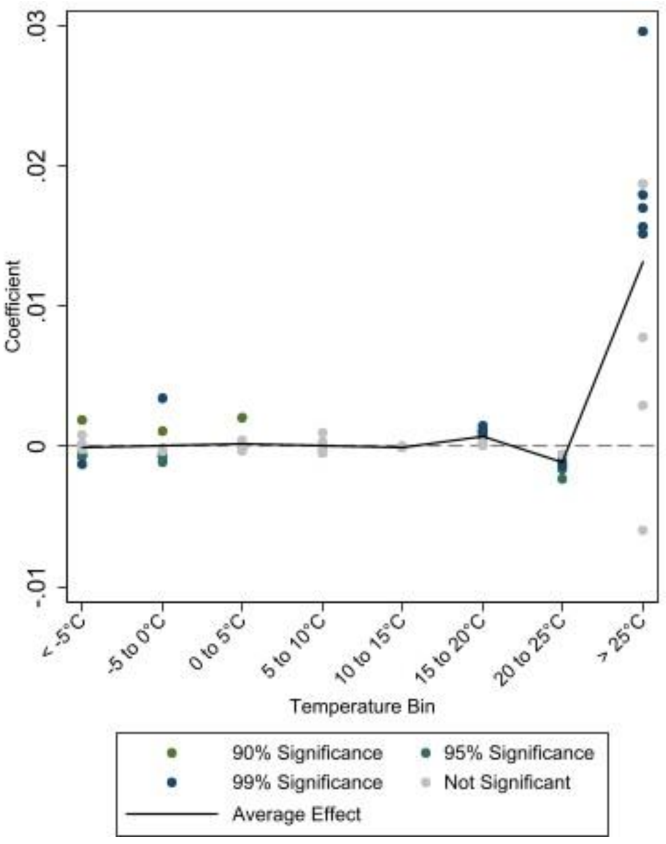

Figure 5: The average and quantile temperature effects to milk yield

Results in Figure 5 show mostly insignificant results, but with some positive significant coefficients, especially towards the extreme upper end of our temperature bins, implying increased milk yields with high temperatures. These results oppose prior literature, such as Ahmed, Tamminen, and Emanuelson (2022), Nardone et al. (2010) and Wankar and Rindhe (2021), stating that milk yield decreases with high temperatures. Instead, these results identify a positive or insignificant effect of one added day of average temperatures above 25˚C. The significant coefficients belong to the 50th, through 90th quantiles, meaning that it is mostly farms with already high milk yields that experience this increase in milk yield with high temperatures.

An increase in milk yield with high temperatures contradicts our main findings in Figure 2, where TFP decreases with high temperatures. An increase in milk yield would presumably increase productivity, as it is an increase in output. This contradiction, while also considering that Figure 5 goes against previous literature, suggests further study of the issue is needed. We thus proceed with studying other mechanisms, possibly interacting with either milk yield or TFP, as mentioned by Harrison, Cullen, and Armstrong (2017) and Dellar et al. (2018), trying to find an explanation to results in Figure 5.

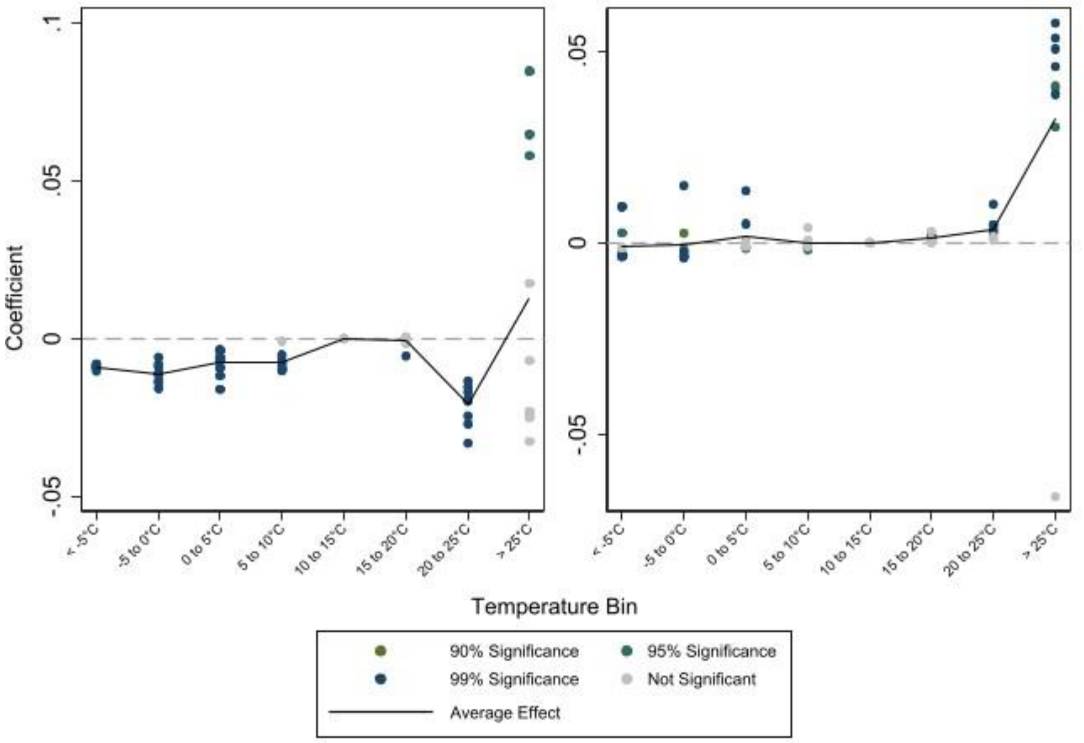

Figure 6: The average and quantile temperature effects to home grown feed quantities and purchased concentrates

Note: On the right-hand side, the analysis is performed with dependent variable home grown feed, on the left -hand side, dependent variable is purchased concentrates

On the left-hand side of Figure 6, we see the impact of our temperature bins on home grown feed, and on the right-hand side the temperature bins' impact on concentrates purchase. Analyzing the left-hand figure, home grown feed, we identify days between 20-25˚C displaying significant and negative coefficients, while days above 25 ˚C remain largely insignificant with some weakly positive coefficients. While this result might seem ambiguous, the coefficients corresponding to bin [≥ 25˚C] are in line with Dellar et al. (2018) showing increased rates of pasture growth with high temperatures.

Studying the right-hand figure, we notice a significant and positive impact to concentrates purchase from one added day with an average temperature above 25 ˚C. As identified in Appendix A - Table 7, significant results mostly stem from the middle quantiles of the distribution, implying that it is mainly farms with average levels of concentrate purchase that increase their concentrates consumption with high temperatures. The only insignificant and negative coefficient belongs to the 10th quantile, with the lowest levels of concentrates purchase.

The increase in concentrates purchase is motivated in literature (Dellar et al. 2018), stating that as heat increases growth rate of pasture, its nutritional uptake does not change, thus reducing its nutritional value per kilogram. This reduced nutritional value would cause incentive for the farmer to substitute some pasture feed with bought concentrates - to ensure the nutritional need of the cow to be met. This would explain both the significant increase in concentrates purchase for most of the sample distribution, as well as the partial increase of home-grown feed.

Furthermore, this provides an explanation for the increase in milk yield, seen in Figure 5, as well as the loss in TFP in Figure 2. With farmers substituting pasture feed with concentrates, a more nutritionally dense feed, it is likely that cows increase their milk production. However, the substitution from home-grown feed to bought feed does incur a significant increase in input costs for the farmer, which the added output in terms of milk does not outweigh, causing the loss to TFP identified in Figure 2.

Numerous previous studies also point at veterinary expenses increasing with temperature. As such we proceed with an analysis of how this fits our model data.

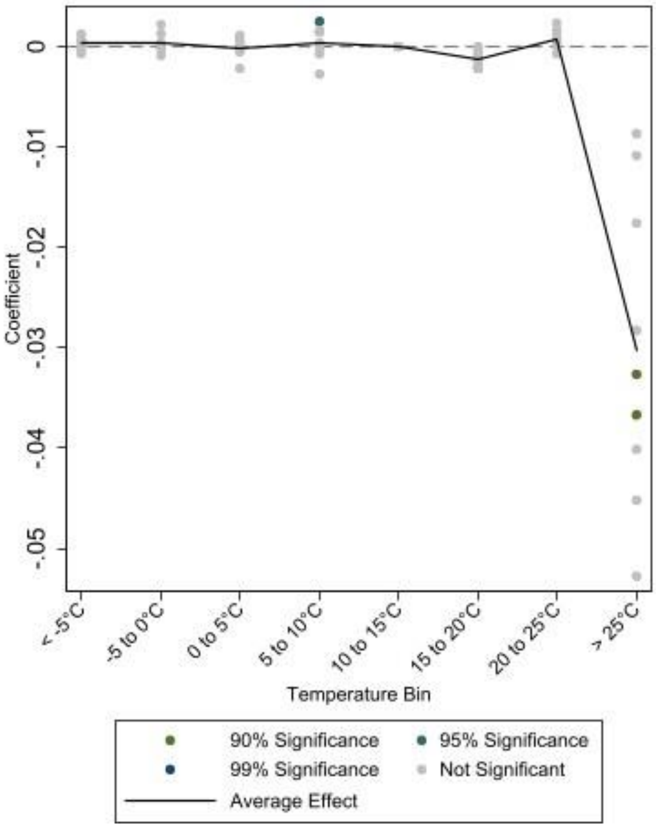

Figure 7: Average and quantile temperature effects to veterinary costs

Studying Figure 7, the lack of significant results is apparent. Apart from two weakly significant coefficients at [≥ 25˚C], all coefficients in this temperature bin are found to be insignificant. This implies that we cannot identify anything but a very weak negative connection between veterinary costs and temperature. While this contradicts previous literature, which establishes a connection between high temperatures and negative impacts to cow health, most of these studies have been performed in controlled settings, to ensure the study of only heat's impact on cows. It is however likely that modern Swedish dairy farms in a real-world setting can adapt stable and pasture climate such that the impact of temperatures to cow health is reduced.

Significant coefficients for bin [≥ 25˚C] come from quantiles 80 and 70. This implies that it is farms with high veterinary costs that see a significant loss to veterinary expenses with increasing temperatures. While the interpretation of these results is not clear, and not explained in previous literature, it would be interesting to look into in future studies.

5.3 Robustness checks

To assess the robustness of our findings, we proceed with estimating two sets of sensitivity analyses. First, we re-estimate the main results using alternative dependent variables, net income and value added, to determine whether the observed effects of temperature extend beyond TFP. Second, we test the sensitivity of our results to temperature bin construction by using narrower intervals (3°C instead of 5°C). These checks ensure that our conclusions are not driven by model specification choices.

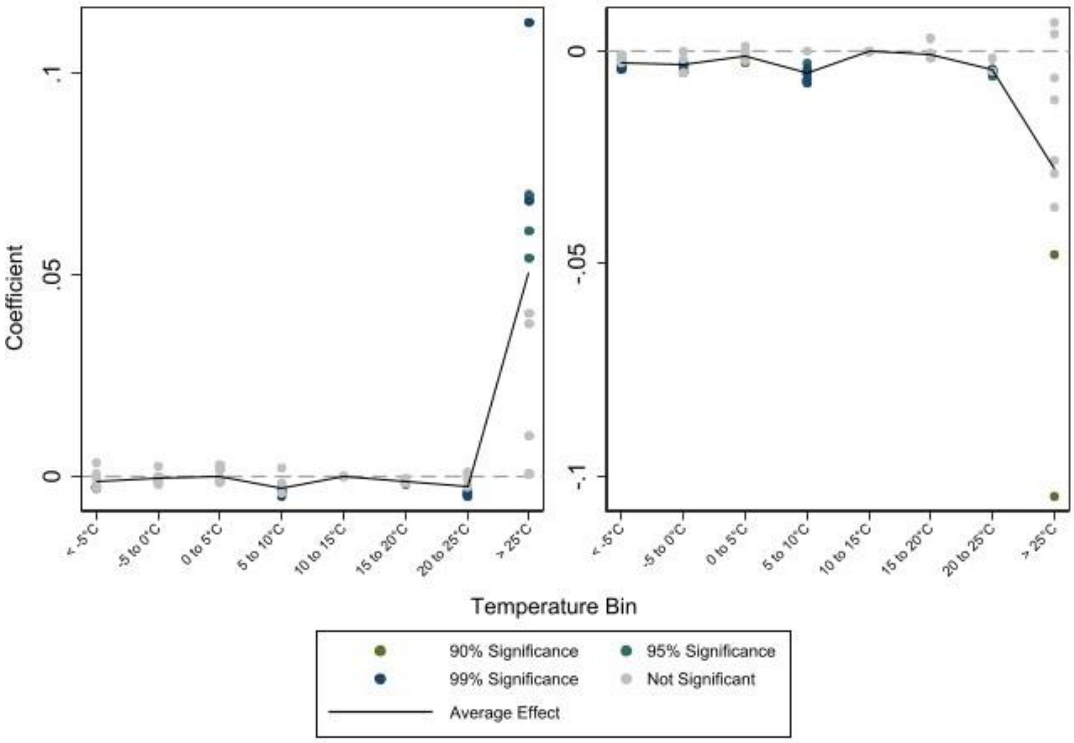

Figure 8: Robustness tests with other dependent variables

Note: On the left-hand side, the main analysis from Figure 2 is performed for dependent variable Farm Net Income, on the right- hand side, dependent variable is Farm Value Added

The left graph, displaying the effect of one added day of temperature above 25˚C on farm net income display results contradicting our main results. Here, one added day of temperatures ≥ 25˚C is connected to an increase in net income. Significant coefficients are found among the upper quantiles, from the 50th all through the 90th quantile, implying that it is mainly highly profitable farm that may increase their profit further with high temperatures. The right-hand side graph, displaying the effect of our temperature bins on farm value added display a trend similar to the one visible in Figure 2, with bin [≥ 25˚C] impacting the dependent variable negatively, but with less significant results than what is found in our main results in Figure 2.

While the TFP analysis provides highly significant results, with negative coefficients, these are lacking in the analysis presented in Figure 6. This implies that TFP, a measure more closely related to efficiency, is more impacted by increasing temperatures, than net profit and value added - which are measures more associated with profitability. This implies that while efficiency is lost at farm level, as temperatures increase, farmers are likely able to buffer impacts to profitability, by strategic altercation of other inputs.

This analysis remains tentative however, and further research is needed to develop a more comprehensive understanding of the issue. Notably, TFP does not capture elements such as subsidies, which in 2018, were a key policy instrument that helped farmers withstand the drought (The Swedish Government Offices 2018). This might possibly explain some of the contradictory behavior observed in these robustness checks. Similarly, off-farm income, which can provide important financial support to farm households, is not reflected in TFP measurements and may also contribute to the contradictory effects identified. These could be interesting aspects for further study, further increasing our understanding of the impact of climate change on farm finances.

Following the main results from Figure 2, we reconstruct the model such that the temperature bins are in increments of 3˚C, instead of 5˚C, and our reference bin being [10-13˚C].

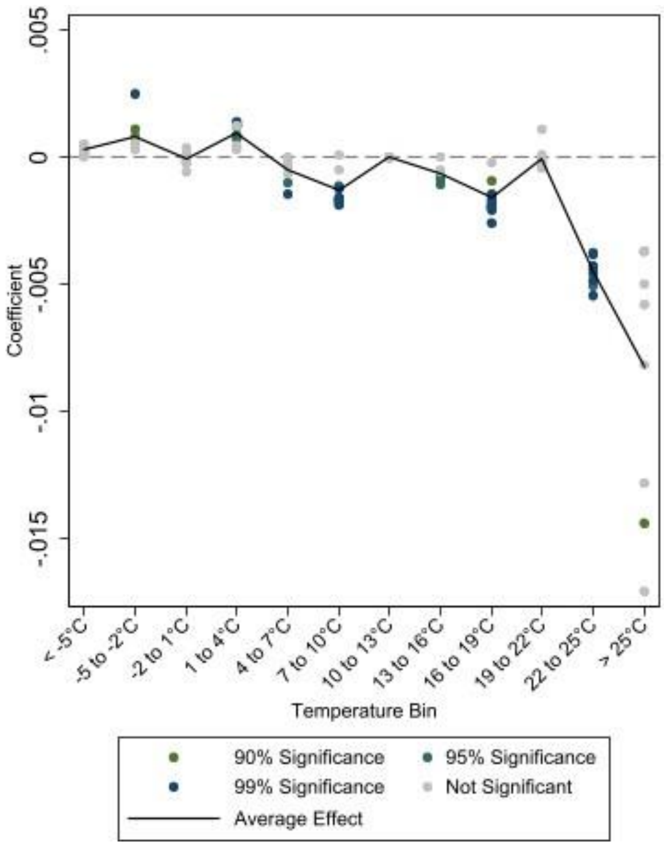

Figure 9: Robustness test with narrower temperature bins (3◦C)

Results from Figure 2 remain broadly consistent; however, some notable differences emerge. Specifically, the negative impact of increasing temperatures on TFP appears to begin already in the [22–25°C] bin, rather than only at the most extreme temperatures. Additionally, the effect observed in the most extreme bin (25°C) is less statistically significant than in the main results. These differences may suggest greater sensitivity to moderately high temperatures than previously indicated, which could not be identified with the broader bins in Figure 2, while also highlighting potential variability in farm-level adaptation or data limitations at the upper end of the temperature distribution.

6. Conclusions

This thesis has investigated the relationship between high temperatures and total factor productivity (TFP) on Swedish dairy farms, employing a RIF-regression approach. While previous studies have shown that cow health, fertility, pasture production, and milk yield can be negatively affected by high temperatures, there has been a significant research gap regarding such effects in a Northern European context. This study has aimed to address that gap by examining whether and how these factors impact Swedish dairy farms.

Results from this study provide important insights into the dynamics of climate change impacts within the Swedish dairy farming sector. Notably, there is a clear association between high temperatures and declines in farm-level TFP. This negative effect seems to be primarily driven by changes in feed consumption patterns: higher temperatures increase levels of externally purchased feed concentrates, which in turn raises production costs.

Previous literature has also suggested that rising temperatures may increase veterinary costs and reduce milk yields. However, this study found no evidence supporting the claim made by Hughes et al. (2022) and Wankar and Rindhe (2021) that veterinary expenses are significantly affected by heat stress. A small positive effect on milk yield was observed, possibly reflecting the increased use of concentrates at elevated temperatures. Nevertheless, this yield gain did not offset the higher feed costs, and the results remained robust despite these variations.

Moreover, this study is among the first to explore the distributional effects of climate change on farm-level TFP. Consistent with Moghaddam et al. (2024), the findings suggest that each additional day above 25°C disproportionately reduces TFP for lower-performing farms compared to higher-performing ones. This raises concerns about growing inequality among farms as climate change progresses.

These findings are foundational, as they represent the first empirical assessment of the financial implications of climate change on dairy production in Sweden and the broader northern European region. While some prior studies have highlighted potential benefits of warming temperatures in Scandinavia, this study demonstrates that significant risks to the farming system also exist.

The results have clear policy implications. Since feed-related costs are identified as the primary driver of production losses during heat events, targeted mitigation strategies could be developed to help farmers cope with such conditions. Possible measures include introducing more heat-tolerant ley species and implementing support programs aimed specifically at feed acquisition during heatwaves.

Additionally, this thesis provides the first comprehensive comparison of how extreme temperatures affect conventional and organic milk production. The results indicate that organic farms exhibit greater variability and less consistent impacts, suggesting a high degree of heterogeneity within this group. This heterogeneity presents a valuable opportunity for future research. Importantly, these findings imply that while conventional farms may benefit from targeted policies—such as support for home-grown feed production or financial assistance during climate stress, similar policies may be less effective for organic farms due to their diverse production systems.

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Popular Science Summary

As global temperatures rise, the effects of climate change are becoming increasingly apparent, even in regions previously considered less vulnerable. This study investigates how high temperatures affect the productivity of Swedish dairy farms, using detailed data from 2002 to 2021. By focusing on the number of days with average temperatures above 25°C, the study explores the distributional effects of heat on farm performance.

The results reveal that high temperatures are associated with a decline in total factor productivity (TFP) among Swedish dairy farms. However, this effect is not evenly distributed across the sector. Farms with lower baseline productivity, as well as organic farms, are more adversely affected than their higher-performing or conventional counterparts. This suggests that climate change may exacerbate existing inequalities within the dairy farming sector.

While productivity declines, milk yields show a slight increase during hot periods, however. This result, contradictory as it may seem, appears to stem from increased purchases of concentrated feed, which farmers likely use to compensate for the reduced quality of pasture during heat events. However, the cost of this additional input outweighs the gains in output, leading to a net loss in overall productivity. No significant evidence was found that high temperatures increase veterinary costs, which contrasts with findings from earlier studies in warmer climates.

In summary, this study highlights that while Swedish dairy farms are already being affected by rising temperatures, the consequences vary significantly depending on farm characteristics. These findings have important implications for agricultural policy. Targeted support—such as feed subsidies, the development of heat-tolerant forage crops, or tailored advisory services—may be necessary to protect the most vulnerable farms and ensure the long-term resilience of Sweden's dairy sector in the face of climate change.

Appendices

A. Regression tables

Table 5: RIF Regressions Estimates - Corresponding to Figure 2

	Quantile								
Mean Temp (°C)	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**
< -5	0.0009**	0.0009***	0.0009***	0.0008***	0.0005*	0.0009***	0.0007*	0.0007	0.0008
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0006)
-5 to 0	0.0004	0.0006*	0.0006*	0.0005	0.0004	0.0006	0.0004	0.0007	0.0015**
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0007)
0 to 5	0.0011**	0.0012***	0.0013***	0.0011***	0.0008**	0.0009**	0.0006	0.0007	0.0007
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0007)
5 to 10	-0.0017***	-0.0012***	-0.0012***	-0.0010***	-0.0009**	-0.0006*	-0.0005	-0.0003	-0.0004
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0007)
15 to 20	-0.0017***	-0.0011***	-0.0009***	-0.0007***	-0.0008***	-0.0007***	-0.0006**	-0.0004	-0.0004
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0005)
20 to 25	-0.0009*	-0.0008**	-0.0009**	-0.0012***	-0.0011***	-0.0010***	-0.0010**	-0.0012**	-0.0004
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0007)
> 25	-0.0124*	-0.0164***	-0.0121**	-0.0135**	-0.0159***	-0.0177***	-0.0246***	-0.0204**	-0.0332***
	(0.0072)	(0.0060)	(0.0056)	(0.0056)	(0.0058)	(0.0062)	(0.0068)	(0.0080)	(0.0121)

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: RIF Regressions Estimates - Corresponding to Figure 3

	Quantile								
Mean temp (°C)	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**
Conventional farms									
<-5	0.0009*	0.0007*	0.0005	0.0005	0.0005*	0.0006*	0.0007	0.0006	0.0010
	(0.0005)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)	(0.0007)
-5–0	0.0000	0.0001	0.0001	0.0001	0.0001	0.0005	0.0003	0.0004	0.0003
	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0007)
0–5	0.0010*	0.0009*	0.0009**	0.0007**	0.0006*	0.0007*	0.0005	0.0004	0.0002
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0008)
5–10	-0.0019***	-0.0015***	-0.0017***	-0.0015***	-0.0012***	-0.0009**	-0.0008	-0.0010*	-0.0009
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0008)
15–20	-0.0016***	-0.0011***	-0.0013***	-0.0011***	-0.0012***	-0.0010***	-0.0007**	-0.0012***	-0.0003
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0005)
20–25	-0.0006	-0.0007	-0.0007	-0.0012***	-0.0013***	-0.0012***	-0.0008	-0.0017***	-0.0012
	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0008)
>25	-0.0095	-0.0085	-0.0185***	-0.0120*	-0.0121*	-0.0182**	-0.0256***	-0.0202**	-0.0155
	(0.0086)	(0.0089)	(0.0070)	(0.0072)	(0.0070)	(0.0084)	(0.0087)	(0.0091)	(0.0123)
Organic farms									
<-5	0.0027***	0.0027***	0.0016**	0.0013*	0.0014*	0.0009	0.0012	0.0007	-0.0018
	(0.0010)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0011)	(0.0017)
-5–0	0.0031***	0.0030***	0.0025***	0.0015	0.0018*	0.0019*	0.0025**	0.0032**	0.0009
	(0.0012)	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0014)	(0.0017)
0–5	0.0032***	0.0033***	0.0024**	0.0018*	0.0023**	0.0017*	0.0021**	0.0014	-0.0005
	(0.0012)	(0.0010)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0013)	(0.0019)
5–10	0.0002	0.0008	0.0000	0.0002	0.0006	0.0000	0.0010	0.0002	-0.0018
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0012)	(0.0015)	(0.0019)
15–20	-0.0015*	0.0004	0.0008	0.0002	0.0006	0.0005	0.0009	0.0004	0.0000
	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0009)	(0.0011)	(0.0015)
20–25	0.0001	-0.0011	-0.0017	-0.0016	-0.0011	-0.0016	-0.0004	-0.0002	-0.0016
	(0.0014)	(0.0012)	(0.0011)	(0.0010)	(0.0012)	(0.0011)	(0.0011)	(0.0016)	(0.0018)
>25	-0.0274	-0.0151	-0.0238*	-0.0295*	-0.0282*	-0.0331**	-0.0283	-0.0692***	0.0040
	(0.0172)	(0.0124)	(0.0134)	(0.0150)	(0.0151)	(0.0168)	(0.0178)	(0.0257)	(0.0164)

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: RIF Regressions Estimates - Corresponding to Figure 4

	Quantile								
Mean temp (°C)	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**
< -5	-0.0013***	-0.0007**	-0.0007**	-0.0005**	-0.0002	-0.0000	0.0002	0.0008	0.0019*
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0006)	(0.0010)
-5 to 0	-0.0011**	-0.0008**	-0.0007**	-0.0006**	-0.0005*	-0.0003	-0.0001	0.0011*	0.0034***
	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0006)	(0.0010)
0 to 5	-0.0003	0.0002	-0.0000	-0.0001	-0.0001	-0.0000	0.0001	0.0005	0.0021*
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0006)	(0.0011)
5 to 10	0.0003	0.0000	0.0002	-0.0002	-0.0002	-0.0004	-0.0005	0.0001	0.0010
	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0006)	(0.0011)
15 to 20	0.0015***	0.0011***	0.0011***	0.0008***	0.0007***	0.0003	0.0002	0.0002	0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)	(0.0008)
20 to 25	-0.0009*	-0.0006	-0.0006**	-0.0006*	-0.0012***	-0.0013***	-0.0014***	-0.0016**	-0.0023**
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0006)	(0.0011)
> 25	0.0297***	0.0180***	0.0171***	0.0152***	0.0157***	0.0078	0.0029	-0.0060	0.0188
	(0.0080)	(0.0059)	(0.0053)	(0.0049)	(0.0050)	(0.0057)	(0.0071)	(0.0104)	(0.0183)

Notes: Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 8: RIF Regressions Estimates - Corresponding to Figure 5

Mean temp (C°)	**Quantiles**								
	90	80	70	60	50	40	30	20	10
Purchase Concentrates									
< -5	-0.0030***	-0.0031***	-0.0036***	-0.0036***	-0.0033***	-0.0033***	-0.0012	0.0026**	0.0094***
	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0009)	(0.0013)	(0.0033)
-5 to 0	-0.0023***	-0.0025***	-0.0036***	-0.0035***	-0.0036***	-0.0039***	-0.0017*	0.0025*	0.0149***
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0009)	(0.0013)	(0.0035)
0 to 5	-0.0007	-0.0006	-0.0014**	-0.0009	-0.0009	-0.0015*	0.0006	0.0049***	0.0136***
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0010)	(0.0014)	(0.0036)
5 to 10	-0.0011	-0.0004	-0.0013*	-0.0006	-0.0004	-0.0019**	-0.0005	0.0006	0.0040
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0010)	(0.0014)	(0.0036)
15 to 20	0.0017***	0.0010*	0.0010**	0.0017***	0.0018***	0.0008	0.0004	0.0000	0.0030
	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0010)	(0.0026)
20 to 25	0.0046***	0.0046***	0.0032***	0.0037***	0.0025***	0.0006	0.0008	0.0015	0.0101***
	(0.0009)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0009)	(0.0010)	(0.0015)	(0.0038)
> 25	0.0301**	0.0533***	0.0572***	0.0459***	0.0386***	0.0504***	0.0404**	0.0408*	-0.0661
	(0.0140)	(0.0120)	(0.0117)	(0.0116)	(0.0126)	(0.0139)	(0.0166)	(0.0236)	(0.0618)
Home Feed									
< -5	-0.0082***	-0.0080***	-0.0083***	-0.0093***	-0.0088***	-0.0087***	-0.0096***	-0.0103***	-0.0095***
	(0.0013)	(0.0012)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0012)	(0.0015)	(0.0022)
-5 to 0	-0.0059***	-0.0080***	-0.0089***	-0.0108***	-0.0115***	-0.0113***	-0.0133***	-0.0139***	-0.0157***
	(0.0014)	(0.0012)	(0.0011)	(0.0011)	(0.0010)	(0.0011)	(0.0013)	(0.0016)	(0.0024)
0 to 5	-0.0037**	-0.0035***	-0.0038***	-0.0060***	-0.0071***	-0.0070***	-0.0093***	-0.0117***	-0.0161***
	(0.0015)	(0.0013)	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0013)	(0.0017)	(0.0025)
5 to 10	-0.0101***	-0.0100***	-0.0094***	-0.0096***	-0.0087***	-0.0077***	-0.0072***	-0.0052***	-0.0008
	(0.0015)	(0.0013)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0013)	(0.0016)	(0.0024)
15 to 20	-0.0012	0.0001	0.0003	0.0003	0.0004	0.0006	-0.0002	-0.0014	-0.0056***
	(0.0011)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0010)	(0.0012)	(0.0018)
20 to 25	-0.0134***	-0.0153***	-0.0169***	-0.0193***	-0.0193***	-0.0199***	-0.0244***	-0.0270***	-0.0331***
	(0.0015)	(0.0013)	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0014)	(0.0017)	(0.0026)
> 25	-0.0235	-0.0232	-0.0326	-0.0249	-0.0069	0.0176	0.0581**	0.0647**	0.0848**
	(0.0250)	(0.0218)	(0.0202)	(0.0195)	(0.0185)	(0.0191)	(0.0226)	(0.0281)	(0.0418)

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: RIF Regressions Estimates - Corresponding to Figure 6

	Quantile								
Mean temp (°C)	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**
< -5	0.0001	0.0004	-0.0002	0.0005	0.0006	0.0006	0.0012	0.0004	-0.0006
	(0.0015)	(0.0011)	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0014)	(0.0018)	(0.0027)
-5 to 0	-0.0009	0.0004	-0.0003	-0.0001	-0.0002	0.0003	0.0013	0.0022	0.0001
	(0.0016)	(0.0012)	(0.0010)	(0.0010)	(0.0011)	(0.0012)	(0.0014)	(0.0019)	(0.0029)
0 to 5	-0.0022	-0.0003	-0.0004	0.0000	0.0000	0.0004	0.0011	0.0007	-0.0005
	(0.0017)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0015)	(0.0020)	(0.0030)
5 to 10	-0.0007	0.0025**	0.0014	0.0015	0.0003	0.0004	0.0016	-0.0002	-0.0028
	(0.0017)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0015)	(0.0020)	(0.0030)
15 to 20	-0.0021*	0.0000	-0.0004	-0.0012	-0.0013	-0.0012	-0.0008	-0.0021	-0.0017
	(0.0012)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0011)	(0.0015)	(0.0022)
20 to 25	-0.0007	0.0006	0.0001	0.0006	0.0015	0.0009	0.0016	0.0023	0.0001
	(0.0018)	(0.0012)	(0.0011)	(0.0011)	(0.0012)	(0.0013)	(0.0016)	(0.0021)	(0.0031)
> 25	-0.0401	-0.0367*	-0.0326*	-0.0282	-0.0176	-0.0086	-0.0108	-0.0527	-0.0452
	(0.0285)	(0.0204)	(0.0184)	(0.0183)	(0.0190)	(0.0206)	(0.0254)	(0.0339)	(0.0509)

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10: RIF Regressions Estimates - Corresponding to Figure 7

	Quantile								
Mean temp (°C)	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**
≤-5	-0.0013	-0.0019	-0.0017	-0.0026*	-0.0023	-0.0020	0.0004	0.0010	0.0036
	(0.0015)	(0.0014)	(0.0014)	(0.0015)	(0.0016)	(0.0017)	(0.0022)	(0.0028)	(0.0042)
-5-0	0.0027	-0.0004	-0.0017	-0.0021	-0.0018	-0.0031*	-0.0016	-0.0030	-0.0021
	(0.0018)	(0.0016)	(0.0015)	(0.0016)	(0.0017)	(0.0018)	(0.0023)	(0.0030)	(0.0047)
0-5	0.0011	0.0010	-0.0002	-0.0005	-0.0002	-0.0007	0.0031	0.0038	0.0018
	(0.0016)	(0.0016)	(0.0015)	(0.0017)	(0.0018)	(0.0020)	(0.0025)	(0.0032)	(0.0051)
5-10	-0.0030	-0.0064***	-0.0069***	-0.0074***	-0.0074***	-0.0085***	-0.0070***	-0.0081**	-0.0066
	(0.0019)	(0.0017)	(0.0015)	(0.0016)	(0.0016)	(0.0018)	(0.0023)	(0.0031)	(0.0047)
15-20-6	-0.0039***	-0.0041***	-0.0038***	-0.0039***	-0.0028**	-0.0028**	-0.0027	-0.0041*	-0.0036
	(0.0012)	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0017)	(0.0024)	(0.0039)
20-25	-0.0059***	-0.0079***	-0.0087***	-0.0094***	-0.0084***	-0.0088***	-0.0074***	-0.0044	-0.0015
	(0.0018)	(0.0016)	(0.0017)	(0.0017)	(0.0017)	(0.0021)	(0.0026)	(0.0034)	(0.0056)
≥25	-0.0205	-0.0266	-0.0162	0.0125	0.0024	-0.0208	-0.0330	-0.0844	-0.0742
	(0.0342)	(0.0310)	(0.0320)	(0.0292)	(0.0323)	(0.0369)	(0.0428)	(0.0645)	(0.0919)

Notes: Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 11: RIF Regressions Estimates - Corresponding to Figure 8

	Quantile								
Mean temp (˚C)	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**
≤-5	0.0020***	0.0021***	0.0021***	0.0020***	0.0015***	0.0015***	0.0012***	0.0006	0.0004
	(0.0005)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0008)
-5- -2	0.0025***	0.0021***	0.0022***	0.0021***	0.0020***	0.0020***	0.0013***	0.0015***	0.0024***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0008)
-2-1	0.0013**	0.0017***	0.0017***	0.0017***	0.0013***	0.0010**	0.0009*	0.0003	0.0003
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0009)
1-4	0.0032***	0.0029***	0.0030***	0.0026***	0.0022***	0.0020***	0.0014***	0.0009*	0.0012
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0007)
4-7	0.0004	0.0006*	0.0009**	0.0014***	0.0012***	0.0010**	0.0008*	0.0003	-0.0001
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0008)
10-13	0.0019***	0.0016***	0.0015***	0.0017***	0.0014***	0.0011**	0.0010	0.0004	-0.0001
	(0.0007)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0007)	(0.0011)
13-16	0.0008*	0.0009**	0.0010***	0.0009**	0.0007*	0.0004	0.0002	-0.0001	-0.0001
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0006)	(0.0009)
16-19	-0.0007	-0.0004	-0.0003	-0.0002	-0.0003	-0.0004	-0.0004	-0.0005	-0.0003
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0010)
19-22	0.0015***	0.0013**	0.0014***	0.0014***	0.0011**	0.0014***	0.0010*	0.0003	0.0010
	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0006)	(0.0009)
22-25	-0.0025*	-0.0021**	-0.0022**	-0.0028***	-0.0028**	-0.0042***	-0.0039***	-0.0040**	-0.0052**
	(0.0013)	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0012)	(0.0014)	(0.0017)	(0.0023)
≥25	-0.0021	-0.0066	-0.0022	-0.0020	-0.0046	-0.0042	-0.0139*	-0.0124	-0.0172
	(0.0080)	(0.0075)	(0.0067)	(0.0061)	(0.0069)	(0.0072)	(0.0081)	(0.0094)	(0.0140)

Notes: Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 12: RIF Regressions Estimates - Corresponding to Figure 9

Mean temp (C°)	**Quantiles**								
	90	80	70	60	50	40	30	20	10
Net Income									
< -5	-0.0028	-0.0028*	-0.0024*	-0.0030**	-0.0026*	-0.0022	-0.0005	0.0006	0.0034
	(0.0020)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0015)	(0.0019)	(0.0025)	(0.0037)
-5 to 0	0.0025	-0.0000	-0.0012	-0.0015	-0.0011	-0.0021	-0.0008	-0.0012	-0.0000
	(0.0022)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0020)	(0.0026)	(0.0039)
0 to 5	-0.0008	-0.0005	-0.0012	-0.0014	-0.0010	-0.0012	0.0018	0.0028	0.0018
	(0.0023)	(0.0017)	(0.0016)	(0.0015)	(0.0015)	(0.0017)	(0.0021)	(0.0027)	(0.0041)
5 to 10	0.0021	-0.0021	-0.0030*	-0.0038**	-0.0040***	-0.0049***	-0.0036*	-0.0041	-0.0016
	(0.0023)	(0.0017)	(0.0016)	(0.0015)	(0.0015)	(0.0017)	(0.0021)	(0.0027)	(0.0041)
15 to 20	-0.0009	-0.0016	-0.0016	-0.0019*	-0.0011	-0.0009	-0.0006	-0.0015	-0.0005
	(0.0016)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0015)	(0.0020)	(0.0030)
20 to 25	0.0005	-0.0027	-0.0041**	-0.0050***	-0.0044***	-0.0047***	-0.0036*	-0.0007	0.0010
	(0.0024)	(0.0018)	(0.0016)	(0.0016)	(0.0016)	(0.0018)	(0.0022)	(0.0029)	(0.0043)
> 25	0.113***	0.0699**	0.0610**	0.0683***	0.0542**	0.0405	0.0379	0.0007	0.0102
	(0.0383)	(0.0289)	(0.0265)	(0.0259)	(0.0260)	(0.0285)	(0.0354)	(0.0464)	(0.0697)
Value Added									
< -5	-0.0007	-0.0024**	-0.0035***	-0.0033***	-0.0033***	-0.0042***	-0.0040***	-0.0026	-0.0014
	(0.0015)	(0.0011)	(0.0011)	(0.0010)	(0.0011)	(0.0012)	(0.0014)	(0.0020)	(0.0031)
-5 to 0	-0.0000	-0.0018	-0.0026**	-0.0032***	-0.0035***	-0.0049***	-0.0048***	-0.0039*	-0.0050
	(0.0015)	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0013)	(0.0015)	(0.0021)	(0.0032)
0 to 5	0.0012	-0.0001	-0.0001	-0.0010	-0.0010	-0.0021	-0.0026*	-0.0015	-0.0015
	(0.0016)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0013)	(0.0016)	(0.0022)	(0.0034)
5 to 10	0.0001	-0.0029**	-0.0041***	-0.0053***	-0.0052***	-0.0068***	-0.0066***	-0.0073***	-0.0074**
	(0.0016)	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0013)	(0.0016)	(0.0022)	(0.0034)
15 to 20	-0.0005	-0.0007	-0.0007	-0.0015*	-0.0013	-0.0015	-0.0012	-0.0008	0.0030
	(0.0012)	(0.0009)	(0.0009)	(0.0008)	(0.0009)	(0.0010)	(0.0011)	(0.0016)	(0.0025)
20 to 25	-0.0017	-0.0041***	-0.0046***	-0.0051***	-0.0044***	-0.0049***	-0.0045***	-0.0058**	-0.0047
	(0.0017)	(0.0013)	(0.0012)	(0.0012)	(0.0012)	(0.0014)	(0.0016)	(0.0023)	(0.0035)
> 25	0.0068	0.0042	-0.0114	-0.0062	-0.0287	-0.0367	-0.0479*	-0.0257	-0.105*
	(0.0271)	(0.0209)	(0.0200)	(0.0195)	(0.0199)	(0.0227)	(0.0267)	(0.0374)	(0.0576)

Notes: Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 13: RIF Regressions Estimates - Corresponding to Figure 10

	Quantiles								
Mean temp (˚C)	**90**	**80**	**70**	**60**	**50**	**40**	**30**	**20**	**10**
≤-5	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0010
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0010)
-5 to -2	0.0010	0.0000	0.0010	0.0000	0.0000	0.0010*	0.0000	0.0010*	0.0030***
	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0010)	(0.0010)
-2 to 1	-0.0010	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000
	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0010)
1 to 4	0.0010**	0.0010***	0.0010***	0.0010**	0.0010*	0.0010*	0.0000	0.0000	0.0010
	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0010)
4 to 7	-0.0010***	-0.0010**	-0.0010	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000
	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0010)
7 to 10	-0.0020***	-0.0020***	-0.0020***	-0.0020***	-0.0020***	-0.0010***	-0.0010**	-0.0000	0.0000
	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0010)	(0.0010)
13 to 16	-0.0010**	-0.0010*	-0.0010	-0.0010**	-0.0010**	-0.0010**	-0.0010**	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)
16 to 19	-0.0030***	-0.0020***	-0.0020***	-0.0020***	-0.0020***	-0.0020***	-0.0010***	-0.0010*	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0010)
19 to 22	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000	0.0010
	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0010)	(0.0010)
22 to 25	-0.0040***	-0.0040***	-0.0040***	-0.0050***	-0.0040***	-0.0050***	-0.0050***	-0.0040***	-0.0050**
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0020)
≥25	-0.0040	-0.0080	-0.0040	-0.0040	-0.0060	-0.0050	-0.0140*	-0.0130	-0.0170
	(0.0080)	(0.0060)	(0.0060)	(0.0060)	(0.0060)	(0.0070)	(0.0070)	(0.0090)	(0.0130)

Notes: Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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