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Regional analysis of the potential of selecting for improved resilience and efficiency traits to increase productivity and sustainability of European cattle system

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- X **PU:** Public (must be available on the website)
- ☐ **CO:** Confidential, only for members of the consortium (including the Commission Services)
- ☐ **CI:** Classified, as referred to in Commission Decision 2001/844/EC

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1. Summary

In this deliverable, the results of an assessment of heat and drought impacts on the resilience and efficiency of current EU cattle systems are presented (Annex 1), and the potential future production potential of different EU dairy farm types, through the use of regionally aggregated, spatially explicit, future forage yield data (Annex 2). As a final step, the impact of certification (such as organic), on economic efficiency of dairy farms was assessed (Annex 3).

It was originally planned that an assessment of selecting for improved resilience and efficiency traits would be undertake through this deliverable. However, the main database constructed and utilised did not contain breed specific data. Therefore, specific breeding objectives and their potential could not be analysed through this method, and a farm systems perspective was taken, assuming that breed and selection traits would be made within a system needs perspective.

The first section of this deliverable utilises the dairy database constructed and available as Deliverable 1.2. It was originally envisaged that this database would comprise data from many different sources such as Multisward, Dairyman, Cantogether or other recent projects with cattle analysis, however, to maintain a consistent database with an identical depth of detail at multiple scales (e.g. NUTS regions across Europe), the database was constructed using FADN data and enhanced with climatic and subsequently forage and crop production data.

The following sections provide a detailed analysis of the resilience and efficiency of dairy farms, building on Deliverable 1.1, and identifying the future potential productivity of farms under climate change. Whilst some systems may experience greater stress from climate impacts and require selection for more robust traits that can for example, withstand periods of less forage availability, other regions may see enhanced productivity, For example in Scandinavia, the growing season is likely to lengthen and therefore breeds that can better utilise grazing areas, rather than a mixed ration in the barn may become more appropriate. However, this need for selection, and the potential for greater R&E is dependent on the identification of local needs and priorities, a wide ranging approach is not likely to achieve success. Ongoing work in WP6, linked to WP4 and 5 will examine this potential in more depth and help identify traits that increase the productivity and sustainability of European cattle systems.

2. Introduction

European cattle farming operates at a high level of efficiency, but for the future this will largely depend on what are the impacts of heat stress or drought. How will the currently varying EU dairy farm types be impacted by changes in climate and forage production. Can different farm types mitigate against potentially negative impacts or will some systems or regions benefit from climate change? Does system or product certification result such as being organic in a more economically efficient enterprise? All these questions help to determine the traits and system re-designs on farm level that can ensure the EU cattle sector remains efficient and resilient to both current and future challenges.

3. Results

3.1. Results 1

Influence of climate stress on technical efficiency and economic downside risk exposure of EU dairy farms are presented in Annexe 1

3.2. Results 2

Climate change impacts on the productivity of EU dairy farms are presented in Annexe 2

3.3. Results 3

Does organic certification make economic sense for dairy farmers in Europe? - A latent class counterfactual analysis are presented in Annexe 3

4. Conclusions

The first section assesses the influence of heat and drought stress on the economic performance of dairy cow systems across the EU. Climatic data available from the Gridded Agro-Meteorological data in Europe were combined with dairy enterprise data from the Farm Accountancy Data Network, resulting in a dataset of 4,412 farms in 22 EU countries over the period 2007-2013. Since the performance of dairy farms can be strongly influenced by the context in which they operate, farms were grouped into areas representing similar climatic conditions through the use of a Latent Class Analysis model. Five lowland classes (North Atlantic, West Atlantic, Boreal, Continental, and South) and one upland class were assessed. Technical efficiency (TE) and economic downside risk were used as performance indicators against which the effect of climatic stress factors is evaluated. Technical efficiency was estimated using a 'true-fixed' effect stochastic frontier model. Economic downside risk was based on gross margin deviations. Regression analysis suggests a significant negative effect of drought and heat stress on TE and on the downside gross margin difference in most climatic classes, with few exceptions. Results imply that both drought and heat stress related issues need to be carefully considered when designing adaptation strategies to address threats to the economic performance of the EU dairy sector.

The majority of European dairy farms are heavily reliant on their own forage production, therefore changes in forage yields due to climate change could severely impact their production and economic performance. Utilising an FADN based database, dairy enterprise output was assessed within a range of climatic regions and across multiple system specifications to account for variation in forages and reliance on external feeds. Incorporation of FAO GAEZ potential yield data for medium and long term time periods allowed an estimation of future forage yields, obtained using a regression equation developed from baseline data. The analysis shows that whilst forage yields and therefore milk production could decline in southern European regions, more northern regions such as Boreal and North Atlantic and upland areas such as the Alps could see up to 12.5% yield increases per hectare. However, this raises questions as to the suitability of these landscapes to support higher stocking rates, so alternatively, less reliance on concentrates maybe a better option. In central and west Atlantic regions changes are expected to be less stark, but changing the current forage crop (e.g. temporary grass to alfalfa) could result in greater productivity, due to better drought tolerance. Changing forage crop could be a successful mitigation decision in areas with a yield reduction, especially as relying on an increase in external feedstuffs to replace lower yielding forages may not be possible due to increasing competition for commodities to feed a growing human population.

The third assessment examines the impact of certification in agriculture, which ensures compliance with tangible standards and should generate economic opportunities for farmers. This study quantifies the economic impacts of organic certification in dairy farming across Europe, using farm-level FADN data from 25 countries while accounting for heterogeneity through a class splitting model. Four distinct classes with dairy farm enterprises operating

under similar production technologies were identified in order to assess gross margin and efficiency differences among certified and non-certified farms. Depending on the nature of the selection bias, treatment effects were estimated either through an endogenous treatment model or through entropy balancing. With the exception of dairy farming in warm regions, the results suggest that organic certification pays off for dairy farmers in Europe, while slightly increasing their economic efficiency. Significant certification effects range from 37% to 70% in terms of profitability gains, and from 3% to 5% in terms of efficiency gains.

In summary, this analysis together with the results of Deliverable 1.1 provides the basis for other components of the project (WP4-6), and indeed other future initiatives, to tailor their R&E selection strategies (WP4) . Furthermore, it allows for investigation into the consequences of different R&E genotypes/breeding decisions on animal performance and farm sustainability (WPs 5, 6) according to the predicted environmental impacts that have been explored in this Deliverable. This deliverable provides an analysis that informs the space within which the "potential" selection solutions, and forms the basis for joining up the dots all the way through to the outputs of the aforementioned other WPs.

5. Partners involved in the work

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6. Annexes

6.1. Annexe 1

Influence of climate stress on technical efficiency and economic downside risk exposure of EU dairy farms

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6.1.1. Abstract

This paper assesses the influence of heat and drought stress on the economic performance of dairy cow systems across the EU. Climatic data available from the Gridded Agro-Meteorological data in Europe were combined with dairy enterprise data from the Farm Accountancy Data Network, resulting in a dataset of 4,412 farms in 22 EU countries over the period 2007-2013. Since the performance of dairy farms can be strongly influenced by the context in which they operate, farms were grouped into areas representing similar climatic conditions through the use of a Latent Class Analysis model. Five lowland classes (North Atlantic, West Atlantic, Boreal, Continental, and South) and one upland class were assessed. Technical efficiency (TE) and economic downside risk were used as performance indicators against which the effect of climatic stress factors is evaluated. Technical efficiency was estimated using a 'true-fixed' effect stochastic frontier model. Economic downside risk was based on gross margin deviations. Regression analysis suggests a significant negative effect of drought and heat stress on TE and on the downside gross margin difference in most climatic classes, with few exceptions. Results imply that both drought and heat stress related issues need to be carefully considered when designing adaptation strategies to address threats to the economic performance of the EU dairy sector.

Keywords: Dairy farms, climate stress, technical efficiency, economic resilience, stochastic frontier analysis.

6.1.2. Introduction

The European dairy sector is the second largest agricultural sector in Europe (EU 2018) and had the largest milk production per head within the G20 nations (EU 2020). Whilst growing EU and global demand is expected to support world dairy markets, the EIP-AGRI Focus Group on Robust and resilient dairy production systems reported that (2018):"A robust and resilient dairy production system should be able to withstand changes from outside like drought and volatile prices". In fact the sector is likely to be increasingly affected by climatic change including higher temperatures and more frequent extreme events such as heat waves, droughts, storms and heavy rainfalls (Ahmad, Diwan et al. 2009, IPCC 2014, IPCC 2019). In dairy systems, this situation is likely to lead to both direct and indirect impacts. With increasing summer

temperatures, heat stress is likely to affect dairy cow productivity more frequently, even in temperate climate regions (Armstrong 1994, Fodor, Foskolos et al. 2018). Heat stress negatively affects dairy cattle welfare and productivity through multiple pathways, including reduced feed intake, increased body temperature and respiratory rate as an attempt to cope with critical environmental temperatures and humidities (Armstrong 1994, Bernabucci, Biffani et al. 2014, Ammer, Lambertz et al. 2018).

These direct consequences on the animal can be further exacerbated through the negative influence of heat and drought on pasture and forage production (Soussana, Graux et al. 2010). The environmental stress of drought and heat on plants is typically related to a loss in yield, but may also affect the roughage nutritional quality. These effects depend on the severity and length of the stress, and on the stage of vegetative development affected (Boyer 1982, Bray 2002). Drought stress events become more common in Europe and in the Mediterranean basin in particular, whilst the increasing occurrence of higher temperature records may worsen impacts of drought (IPCC 2019). The combined effects of heat waves on cattle welfare and on pasture and forage productivity are likely to affect the economic performance of dairy farms. In 2003, for instance, the combination of both heat and drought across Europe led to a widespread decline in farm incomes (Fink, Brücher et al. 2004).

The literature on dairy systems typically analyses the effects of climate on yields or revenues in very specific contexts or countries, and impacts are often measured only for a limited time-period (e.g. Bernabucci, Biffani et al. 2014, Fodor, Foskolos et al. 2018). Moreover, many studies to date lack consideration of the dairy enterprise as an economic unit. Therefore, this paper aims to evaluate the influence of heat and drought stress on the annual performance of dairy cow systems across a large geographic region using balanced dairy enterprise panel data from the Farm Accountancy Data Network (FADN) database (EU-FADN – DG AGRI 2019). Performance is measured in terms of technical efficiency (TE) and economic downside risk, which are often used as economic indicators in the dairy sector since they reflect the capacity of farms to achieve their full and individual specific potential as well as to face with major economic risks (e.g. Madau et al. 2017, Finger et al. 2018).

Technical efficiency characterises farm performance and reflects the ability of a farm to generate output units given the inputs and the state of technology at its disposal (Johansson 2005, Abdulai and Tietje 2007). We assume that climate stress decreases TE through two main pathways. Firstly, dairy cows can be directly affected by heat stress with an immediate drop in milk yield and quality (Hill and Wall 2015). Secondly, both heat and drought stress can affect the quantity and the quality of forage available for dairy cows, causing on one hand a reduced grass availability for grazing herds during the stress period, and on the other hand, potentially impacting yield and quality of forage harvested for the subsequent winter feeding period. The consequent need to purchase externally sourced forage or concentrated feedstuffs may affect the economic performance of dairy enterprises, even if productivity is maintained.

Economic downside risk measures the negative economic impact(s) associated with production risk(s). It is a performance indicator that is of particular importance in the dairy sector where farmers have to deal with high milk quantity, quality and market price volatility (Wolf, Roy Black et al. 2009, Belasco, Schroeder et al. 2010, Henry, Boyer et al. 2016, Finger, Dalhaus et al. 2018). Technical efficiency and economic downside risk are complementary

indicators, where high technical efficiency of farms does not necessarily reduce exposure to economic downside risk (and vice versa), depending on the intensity of input use per dairy cow. In this study, our hypothesis is that both TE and economic downside risk are negatively affected by climate stress.

6.1.3. Material and Methods

6.1.3.1. Data

The analysis of climate impacts on the performance of the EU dairy cow sector was undertaken by combining climatic data available from the Gridded Agro-Meteorological data in Europe (AGRI4CAST) (EU 2019) and the farm accounting data available from the FADN database (EU-FADN – DG AGRI 2019) at a NUTS2 region (e.g. French Alsace region) spatial scale (EU 2019). The software Stata 15.1 (StataCorp 2017) was used in all steps of the analysis for data management and computation.

6.1.3.2. Climatic data

Daily meteorological data for the period 2004 to 2013 was obtained from the Agri4Cast database that comprises daily weather values, including the grid number (location) of each weather station, altitude (m), vapour pressure (hPa), precipitation quantity (mm), and the maximum, minimum and average temperature (°C). The individual weather station data needed to be aggregated to NUTS2 regions in order to match heat and drought information with the anonymised farm data organised by NUTS regions within the FADN data structure. As the approximate altitude of each farm was also available, the climatic data could be allocated to a binary altitude variable, allowing a differentiation between lowland and upland farms (threshold of 600 meters). Missing values, due to a lack of weather station data in a particular region, were derived using the percentage difference between lowland and upland areas at the larger NUTS1 level. The percentage difference was capped to ±25% to prevent inaccurate extreme difference when the initiative value was very close to zero. The corresponding value in the altitude level with missing information at NUTS2 level was adjusted by this percentage difference.

Since the performance of dairy farms can be strongly influenced by the context in which they operate, it is important to cluster farms from regions that are part of a similar environment. Ceglar et al. (2019) defined European climate zones using weather data at NUTS2 level, but their study focused specifically on cropping systems and the variables used to define the different zones were selected for their capacity to discriminate favourable climatic conditions for vegetation growth. In this paper, we postulate a direct effect of weather on forage production but also on health and productivity of dairy cows. Therefore, NUTS2 regions were grouped into classes representing similar climatic conditions (climatic regions) in general terms. The dataset contained 239 lowland and 153 upland NUTS2 regions respectively. Latent Class Analysis (LCA) was used to identify the underlying structure of the data to predict the probability of each lowland region to belong to a specific class (Hagenaars and McCutcheon 2002). Following authors who specified European agro-environmental zones (Metzger 2005, Iyigun, Türkeş et al. 2013, Beck, Zimmermann et al. 2018), in this study the following seasonal and annual temperature variation and precipitation variables were selected for use in the parametrisation:

Maximum summer temperature, minimum winter temperature, annual standard deviation of daily average temperature, number of rainfall days with <1mm and the average daily rainfall.

The Stata command *gsem* with the *lclass* option was used to fit a model with latent classes (Stata 2011) for all NUTS2 regions in lowland areas, with upland areas further identified by their altitude (>600m) given their specificity in terms of dairy system. The number of classes was defined by minimising the Schwarz Bayesian Information Criterion (SBIC) (Schwarz 1978) whilst retaining sample sizes of >200 observations a year. This resulted in 5 lowland classes, whilst all upland farms were grouped into a single class. Therefore, 6 climatic classes were assessed, with the following geographically descriptive names: North Atlantic (NAT), West Atlantic (WAT), Boreal (BOR), Continental (CON), South (SOU) and Upland (UPL).

6.1.3.3. Temperature-humidity index

Temperature-humidity index (THI) is a common indicator to measure potential heat stress in cattle based on environmental temperature and humidity (Johnson 1980, Hahn, Mader et al. 2003). However, the expected threshold above which heat stress can be observed varies greatly in the literature, ranging from 60 to 78 (McDowell 1972, Brügemann, Gernand et al. 2012, Dash, Chakravarty et al. 2016), which is likely due to the large diversity in both methodology and geographical location covered by different studies. An important difference is whether the calculated THI thresholds corresponds to a daily average, daily maximum, daily minimum, to a mix of maximum and minimum values, or more to instantaneous values, either real or derived from the maximum and minimum THI values (Ravagnolo, Misztal et al. 2000, Finger, Dalhaus et al. 2018). Another major difference is the geographical area studied as there is evidence for cattle acclimatisation to heat stress (Dunn, Mead et al. 2014).

Several THI formula have been developed over the past decades (see e.g. Dikmen (2009) for a review). In this study, THI was calculated in three steps, as shown in the following (NRC 1971, Sargent 1980, Oyj 2013):

$$Tdc=240.7263/[7.591386/(\log10(Pw/6.116441))-1] \quad (1)$$

$$RH=10^{[7.591386x((Tdc/(Tdc+240.73))-(Tdb/(Tdb+240.73)))]} \quad (2)$$

$$THI=(1.8xTdb+32)-[(0.55-0.0055xRH)x(1.8+Tdb-26.0] \quad (3)$$

where *Tdc* is the dewpoint, *Pw* is the vapour pressure (hPa), *Tdb* is the dry bulb temperature in °C, and *RH* is the relative humidity in %.

West (2003) and Spiers *et al*. (2004) reported a heat stress impact on milk yield from the third consecutive day of exposure to high THI. In this study, to account for heat stress, the number of occurrences when there were at least 3 consecutive days of exposure to high THI was calculated. Different THI thresholds were primarily assigned to the geographical classes identified by the LCA procedure: A threshold of 60 was selected for NAT and BOR (coolest western classes) in line with estimations by Brügemann *et al.* (2012); 64 was the threshold for WAT, CON, and UPL (average of estimation by Brügemann *et al.* (2012) and Zimbelman, Rhoads et al. (2009)); and 68 was the threshold for SOU as suggested by Bouraoui *et al.*

(2002) under a Mediterranean climate. The threshold of 64 assigned to CON and UPL classes did not allow to assess a significant effect, therefore it was increased to 68.

6.1.3.4. Drought indicator

Water availability in soil is a key factor in forage production (Sepulcre-Canto, Horion et al. 2012), but this information was not available. In this study, precipitation levels were used to predict drought periods as limitations in water availability is partially caused by limited precipitation. Equivalent to the THI calculations, the drought stress was defined as the number of periods from March to September (most critical period for vegetation growth) with a specified minimum number of consecutive dry days. A dry day was defined when daily precipitation was below 3 mm. A drought stress threshold of between 10 to 60 (interval of 10) dry consecutive days was selected in each class at the 75% percentile of the corresponding number of annual dry periods. The process resulted in a cut-off value of 40 consecutive dry days in most of the classes apart from NAT (30 days), and SOU (60 days).

As the drought might induce a delayed effect on the following feeding periods due to decreased forage supplies, a time-lagged drought variable, based on the same thresholds, was also created. This lagged variable was then transformed into a dummy variable, to identify if the previous year was exceptionally dry or not, which was created by selecting 0.3 annual dry periods from March to September at NUTS2 level (average from several weather stations), corresponding to the 90th percentile in NAT, WAT, and CON. This variable was not included for the other classes due to multicollinearity issues.

6.1.3.5. Farm data

Farm data consisted of the FADN data on farm characteristics and production of all ruminant and ruminant-mixed farm types over a ten year period from 2004 to 2013 in 25 EU countries (the most recent data available at request). Only farms with an economically relevant dairy enterprise were retained. As per FADN methodology, farms were defined as dairy specialist with a dairy economic output of at least 35% of the total farm economic output (EU 2014). The selected dataset of farms comprised direct and calculated FADN values, on the basis of the FADN dairy enterprise allocation methodology (EU 2014). Values of EU dairy farms were calculated at the dairy enterprise, per unit of cow and on a forage hectare basis to further characterize and quantify their economic performance.

To allow observation of the same individual (farm) in a given period (year) and to reduce the noise associated with individual heterogeneity, balanced panel data is preferred over unbalanced data (Quayes 2015). This approach is particularly important when the model does not assume technical efficiency to be time-invariant (Gupta and Nguyen 2010). The use of panel data has the advantage to control for the unobservable time-invariant heterogeneity due to omitted variables (e.g. farmers' education level) and thus helps to obtain more accurate inefficiency estimates (Ahn, Lee et al. 2013).

The selected dairy dataset of more than 140,000 observations did not represent a perfect balanced panel database structure and was therefore refined by only retaining farms that occurred continuously within the dataset for seven consecutive years (2007 to 2013). The resulting sub-dataset of ca. 35,000 observations was further reduced after removing severe outliers. Severe outliers (ca. 2,000 observations) for the production function variables, the farm

size (ha), and stocking density [grazing livestock unit (GLU)/ha] were excluded separately for each class using the standard 25th and 75th percentile ± three times the interquartile range. The final dataset contained 6 classes comprising 30,884 observations, representing a sample of 4,412 farms in 22 EU countries over the period 2007-2013. Table 1 reports the descriptive statistics on production, economic and climatic variables of the farms in the 6 climatic zones.

Moreover, in order to obtain a better geographical representativeness of the dairy farms in each class, a weighting factor was created and used in the efficiency and downside risk analysis to weight individual farm observations. The weighting factor was based on the number of farms present in each NUTS2 region in the year 2007 (first year) in the final dataset compared to the number of farms represented in the database in the same year before the data subset was created.

Table 1: Production, economic, and climatic characterization of farms in each class (average of 2007 to 2013)

Class	NAT		WAT		BOR		CON		SOU		UPL	
Description (and countries with NUTS2 regions represented)	Cool and wet, with low temperature variation *(IE, UK)*		Moderate temperature, with warmer summers and cooler winters *(BE, DE, ES, FR, LU, NL, PT, UK)*		Very cold winters, moderate temperature in summers, dry *(FI, SE)*		Warm summers, cold winters *(AT, CZ, DE, EE, FR, LT, LV, PL, SE)*		Hot summers, cool winters *(AT, CY, EL, ES, FR, HU, IT, MT, PT, SI)*		Quite warm summers and cool winters, *(AT, CZ, DE, ES, FR, IT, PL, PT, SE, SI)*	
All observations	2,289		9,478		1,589		12,306		1,799		3,423	
Number of farms	327		1,354		227		1,758		257		489	
Variables	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Output and farm characteristics												
Production (kg/cow)	5,809	1,359	7,259	1,564	8,628	1,235	5,946	1,700	6,894	1,957	6,425	1,516
Milk price (€/dt)	31.9	4.4	35.4	4.9	43.6	4.5	31.4	6.1	38.4	8.6	38.0	7.1
Dairy cows (#)	87	62	67	42	41	27	33	27	61	51	29	20
Specialisation (%)	73	12	72	15	79	12	64	14	71	14	67	14
Farm size (ha)	77	49	77	54	71	39	59	58	49	47	45	38
Forage area (ha)	74	46	59	37	49	29	39	41	38	35	41	36
Share of forage maize (% of farm size)	1.1	4.0	19.0	17.1	0.1	1.4	11.2	11.2	14.1	22.2	4.6	10.5
Stocking density (GLU/ha)	2.09	0.58	2.34	1.16	1.39	0.56	1.84	0.89	4.02	3.66	1.51	0.85
Input costs												
Feed cost (€/cow)	646	287	693	365	1261	514	578	321	1241	631	766	472
Forage cost (€/cow)	142	51	154	88	184	95	108	74	102	85	61	60
Maintenance cost (€/cow)	98	51	158	91	402	199	127	91	93	80	159	98
Labour (AWU[1]/cow)	0.02	0.01	0.02	0.01	0.06	0.03	0.06	0.04	0.04	0.02	0.05	0.02
Land availability (ha/cow)	0.67	0.22	0.69	0.28	1.10	0.44	0.91	0.54	0.60	0.44	1.19	0.74
Other costs (€/cow)	277	127	350	166	589	274	196	151	225	162	273	156
Climate records												

[1] Annual work units.

Maximum summer temperature (°C)	18.0	0.8	22.3	1.4	18.8	1.8	23.4	1.2	28.4	1.9	21.8	2.3
Min winter temperature (°C)	3.2	1.8	2.0	2.5	-10.5	4.2	-3.0	2.7	1.9	3.5	-3.8	2.8
SD of avg temperature (°C)	4.4	0.7	6.1	1.0	9.8	1.4	8.3	1.0	7.3	1.0	7.5	0.8
Rainfall days <1mm (#)	196.3	17.5	240.2	12.5	249.6	12.4	251.0	14.5	282.9	21.5	247.9	21.7
Rainfall (mm/day)	3.0	0.4	2.3	0.4	1.7	0.3	2.0	0.4	2.1	0.7	2.8	0.7
Periods ≥30 cons. dry days (#)	0.22	0.31	0.46	0.42	0.64	0.45	0.35	0.32	0.99	0.64	0.45	0.50
Periods ≥40 consecutive dry days (#)	0.02	0.06	0.14	0.24	0.20	0.18	0.12	0.17	0.52	0.50	0.21	0.34
Periods ≥60 consecutive dry days (#)	0.00	0.01	0.02	0.07	0.03	0.05	0.01	0.04	0.25	0.38	0.06	0.18
Periods ≥3 consecutive hot days - THI 60 days (#)	1.30	0.80	8.11	1.85	3.07	1.53	7.84	2.05	6.32	2.00	5.91	1.92
Periods ≥3 consecutive days - THI 64 days (#)	0.00	0.00	1.03	0.98	0.23	0.58	1.96	1.33	5.00	1.24	1.11	1.19
Periods ≥3 consecutive days - THI 68 days (#)	0.00	0.00	0.02	0.10	0.00	0.00	0.02	0.11	1.60	1.48	0.04	0.33

6.1.3.6. Efficiency analysis

As recommended by Coelli (1995) for the computation of TE scores in an agricultural context, the Stochastic Production Frontier (SF) approach was used in this study. The model separates the one-sided TE component (u_i) from the statistical noise captured by the random error component v_i. This is of utmost importance due to the typical occurrence of data inconsistencies and measurement errors (Coelli 1995). The Cobb-Douglas functional form was selected, with the underlying assumption of constant returns to scale tested in all classes. Constant return to scale means that the relative increase of the output is equal to the relative increase of the allocated production factors.

To estimate TE scores, the Stata command *sfpanel* was used, specifying the *tfe* option for time-varying efficiency with 'true-fixed' effects (Greene 2005). The unobserved individual effects, capturing all unobserved heterogeneity, are fixed (time-invariant) and assumed to be correlated with the regressors. The 'true-fixed' effect model developed by Greene allows changes in observable individual effects over time by disentangling productive unit specific heterogeneity from inefficiency (Wang and Ho 2010, Kutlu, Tran et al. 2019). For the inefficiency term u_{it}, the half-normal distribution is specified, which appears to be an appropriate specification for highly competitive economic sectors (Kumbhakar, Wang et al. 2015), such as the dairy industry (Drescher and Maurer 1999).

The annual production of milk (kg) per dairy cow was used as a dependent variable. Given the absence of information on the physical quantity of inputs in the FADN database, and the lack of full statistical information on the unit cost of the different inputs in each EU country and over time, inputs were expressed in constant monetary values in the model, using 2013 as the base year. The inflation adjustment of input values was undertaken using the Harmonised Index of Consumer Prices (HICP) and the price indices of the means of agricultural production provided by Eurostat (2018, 2019). The latter was used to deflate feed and forage costs, while the other monetary variables, less associated to fertiliser markets, were adjusted by the HICP. Inputs

were also expressed per dairy cow and comprised feed costs (coarse fodder, non-fodder, and concentrate), forage costs (based on seed, fertiliser, and pesticide costs), maintenance costs (machinery, cars, building, and land improvement) and other costs related to milk renewal (herd replacement), contractual work, and veterinary services. The family and hired labour were also included and expressed in annual work units (AWU). Finally, the forage area (ha) allocated to the dairy enterprise by GLU was included to better account for forage availability per dairy cow.

According to Greene (Greene 2005), the 'true-fixed' effect frontier model was parameterised as follows:

$$\ln(\mathrm{PROD}_{it})|_{cl} = \alpha_i|_{cl} + \ln(x_{it})\beta|_{cl} + v_{it}|_{cl} - u_{it}|_{cl} \quad (4)$$

Where PROD_{it} is the production of milk (kg) per dairy cow for farm$_i$ at time$_t$ in a given class$_{cl}$; $|_{cl}$ means that each class *cl* is estimated independently; α_i is the time-invariant unobserved firm-specific (individual) effect; x_{it} is the vector of input variables; β is the vector of coefficients; v_{it} is the random noise term; and u_{it} is the inefficiency term (score from 0 to 1).

The effect of climate conditions on the inefficiency variance function was investigated in the frame of the SF model by controlling for the explanatory factors using the *usigma* option. The inefficiency term u_{it} was thus assumed to be heteroskedastic, with the inefficiency variance expressed as a function of the covariates specified in the *usigma* option (Belotti, Daidone et al. 2013). The inefficiency estimations and identification of their determinants were performed in a single stage process, as undertaken by Kumbakar *et al.* (1991) and Battese and Coelli (1995). This method has the advantage over a two stage estimation process, in that it includes exogenous variables (observed heterogeneity) that may affect the frontier as well as the inefficiency distribution and estimates (Kumbhakar and Lovell 2000, Wang and Schmidt 2002, Belotti, Daidone et al. 2013).

The climatic regressors included in the model were the number of periods of 3 or more consecutive hot days (based on THI 60, 64, or 68); the number of periods of at least 30, 40, or 60 consecutive dry days; and the dummy lagged drought variable. Farm size measured as Utilised Agricultural Area (UAA), dairy specialisation rate, and the share of forage area, were included as control variables in the model due to their potential positive influence on efficiency ((Alvarez and Arias 2004, Bojnec and Latruffe 2013) (Kelly, Shalloo et al. 2013). The share of forage maize area was included in the model as a proxy for more productive land as it is likely to inadvertently increase TE. An indication of whether a farm is organic or not was also included (as dummy: 1=organic). Finally, the price of milk was also controlled for as it is expected to affect efficiency for two reasons, partly due to making fewer efforts to improve TE, and also due to a possible bias correction associated to a possible heterogeneity in input prices across countries. Milk prices are likely to give an indication on input prices due to country specificities in terms of general price level. This assumption is supported by the dataset, where we found a moderate positive correlation between milk prices and input costs of around 0.3 in CON, SOU, and UPL (with almost zero correlation in the other classes). Therefore, efficiency scores of farms located in these classes may be biased and it is essential to control for this possible bias.

As observations may be correlated within a NUTS1 region, due to similar farm systems at that level, the option *vce (cluster)* was used to adjust standard errors (SE), by relaxing the usual requirement of independent observations (Belotti, Hughes et al. 2017). Therefore, correlation within NUTS1 regions was allowed, whilst assuming observations to be independent between regions.

6.1.3.7. Economic downside risk analysis

The economic downside risk was explored by computing the downside gross margin difference (DGMD) per dairy cow as the performance parameter by using the same dataset utilised for the efficiency analysis. Gross margins for all farms were calculated as the revenue (production *x* milk price) minus the sum of feed, forage, maintenance, and other costs. The downside risk was calculated on an annual basis for each individual farm as the difference between the gross margin in year *t* and the average gross margin over the seven year period. As we only look at the downside risk, positive values were treated as null-effects, which implies the dependent variable to be right censored at the zero value. As a significant fraction (49.8%) of the observations had a null value, a Tobit model was selected to deal with this type of data (Tobin 1958). Contrary to the SF model, unobserved heterogeneous variables were not expected to be correlated with the climatic and control regressors, therefore a random-effects model was used (*xttobit* command). The class-specific random-effects Tobit model was specified as follows:

$$DGMD_{it}|_{cl} = x'_{it}\beta|_{cl} + \varepsilon_{it}|_{cl} \quad (5)$$

$$DGMD_{it}|_{cl} = \{0 \text{ if } y_{it}|_{cl} \geq 0\} \quad (6)$$

Where equation (5) indicates that $DGMD_{it}$ is the downside gross margin difference per dairy cow for farm$_i$ at time$_t$ in a given class$_{cl}$; $|_{cl}$ means that each class *cl* is estimated independently; x_{it} is the vector of explanatory variables; β is the vector of coefficients; and ε_{it} is the disturbance term. Equation (6) indicates that the dependent variable is right censored at the zero value, in all classes.

6.1.4. Results

6.1.4.1. Technical efficiency

First of all, our results show that the Cobb-Douglas functional form was appropriate for fitting the SF model with the test for the underlying assumption of constant returns to scale (sum of inputs elasticity=1) being highly significant (***) across all classes. The Wald test was also highly significant (***) in all classes, indicating the explanatory variables were appropriately selected.

The distribution of efficiency scores shows a similar pattern across classes apart from SOU and UPL where the distribution is flatter (Figure 1), meaning that these classes are more heterogeneous in terms of efficiency. Average efficiency scores across the 6 climatic classes are very high, ranging from 0.88 (out of 1) in SOU to 0.96 in NAT.

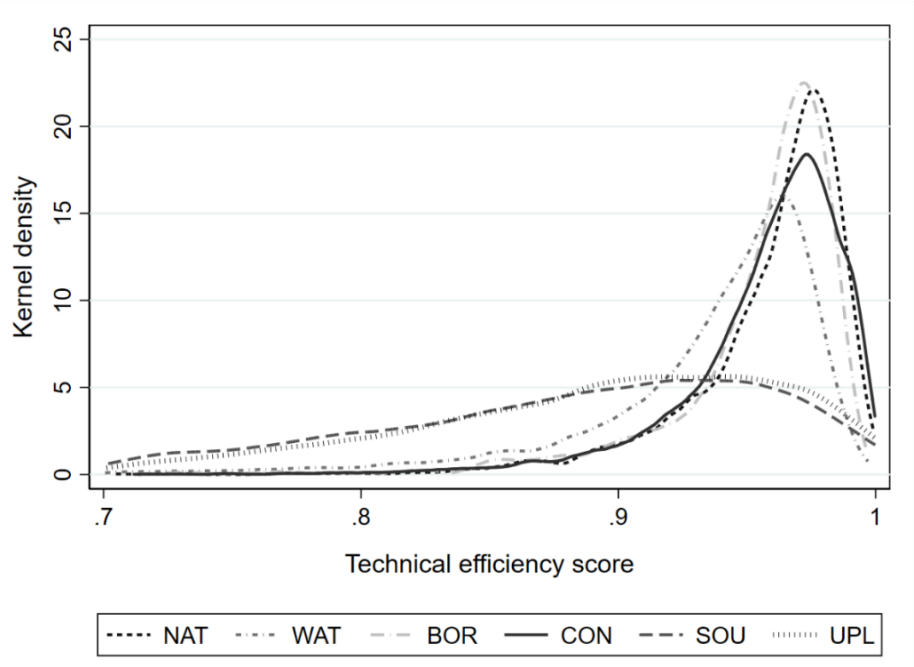

Figure 1: Distribution of efficiency scores in each climatic class

The estimated coefficients for the milk production function are presented in Table 2. The great majority of coefficients had the expected positive sign. Feed cost per dairy cow were a highly significant factor across all classes, though no significant associations were found for forage costs. Labour was significant for all classes, whilst maintenance, land availability, and other costs (milk renewal, contractual work, and veterinary services), were significant for most classes.

Table 2; Milk production function determinants in each climatic class from 2007 to 2013

	NAT		WAT		BOR		CON		SOU		UPL	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Feed [ln(€/cow)]	0.118***	0.026	0.169***	0.018	0.073***	0.002	0.088***	0.004	0.115***	0.026	0.140***	0.008
Forage [ln(€/cow)]	-0.005	0.006	-0.001	0.002	-0.000	0.004	0.004	0.002	0.001	0.010	-0.000	0.005
Maintenance [ln(€/cow)]	0.013*	0.007	0.015***	0.003	0.025***	0.005	0.020***	0.001	0.002**	0.001	0.008	0.008
Labour [ln(awu/cow)]	0.132***	0.015	0.090***	0.016	0.063***	0.008	0.081***	0.015	0.173***	0.037	0.117***	0.027
Land [ln(ha/cow)]	-0.020	0.018	0.084***	0.011	0.007	0.012	0.034***	0.013	0.033***	0.001	0.091***	0.033
Others [ln(€/cow)]	0.048***	0.006	0.056***	0.004	0.027***	0.002	0.029***	0.004	0.020***	0.004	0.002	0.004
Constant (vsigma)	-5.743***	0.246	-6.019***	0.393	-5.737***	0.197	-4.918***	0.112	-45.557***	0.761	-43.519***	0.751
All observations	2,289		9,478		1,589		12,306		1,799		3,423	
Number of farms	327		1,354		227		1,758		257		489	

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1; Dependent variable: Milk production [ln(kg/cow)]

Table 3 presents the determinants of inefficiency, and not efficiency, as the analysis was conducted in a one-stage process. In the WAT, BOR, SOU and UPL classes, drought is significantly and positively associated with inefficiencies in a given year *t*. Otherwise, drought has no significant effect in CON, while it has a delayed significant effect in NAT for year *t+1*. Heat also significantly contributes to inefficiencies in most of the classes, with exceptions in CON and UPL.

The estimated parameters for the control variables suggest that a higher specialisation rate and a higher milk price have a significant effect, reducing or increasing inefficiencies respectively. The effect of farm size on the inefficiency term was not significant across classes apart from BOR where it significantly reduced inefficiency. The share of maize forage was not significant in most classes apart from UPL. Moreover, organic farms appear to be significantly less inefficient than conventional ones in BOR and SOU, though this effect is not confirmed in other classes.

Table 3: Influence of heat and drought stress on technical inefficiency in each climatic class from 2007 to 2013

	NAT		WAT		BOR		CON		SOU		UPL	
Variables	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Drought	-0.736	0.468	0.535**	0.249	0.129***	0.044	0.118	0.893	0.506**	0.232	1.090***	0.269
Lagged drought	0.667***	0.240	-0.012	0.239			0.045	0.563				
Heat	0.695***	0.236	0.304***	0.093	0.150***	0.005	-6.307	6.302	0.179**	0.091	-0.013	0.093
Farm size (ha)	-0.017	0.025	-0.019	0.015	-0.014***	0.005	-0.024	0.019	-0.003	0.003	-0.002	0.001
Specialisation (%)	-0.046	0.029	-0.042***	0.008	-0.059***	0.009	-0.064***	0.014	-0.016**	0.007	-0.033***	0.006
Maize (%)	-0.102	0.078	-0.002	0.005	-0.042	0.037	-0.004	0.018	-0.006	0.004	0.006*	0.003
Milk price (€/dt)	0.010	0.028	0.076***	0.010	0.218***	0.010	0.067**	0.029	0.042***	0.007	0.037***	0.008
Organic (yes=1)	1.280	1.456	0.534	0.412	-1.003***	0.069	-0.166	0.954	-1.107***	0.265	-0.250	0.223
Constant (usigma)	-2.604*	1.445	-3.553***	1.117	-10.126***	0.092	-2.646***	0.985	-3.877***	0.802	-2.825***	0.633
All observations	2,289		9,478		1,589		12,306		1,799		3,423	
Number of farms	327		1,354		227		1,758		257		489	

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1; Dependent variable: [inefficiency term u_i]

6.1.4.2. Economic downside risk

An average of ca. 50% (n=2,217) of the total number of farms (n=4,412) were affected annually by downside risks across all classes. However, this share was quite variable and ranged from ca. 29% in 2007 to 89% in 2009, with a standard deviation of 23% over the seven year period.

The average trend of DGMD per dairy cow is illustrated in Figure 2. A similar pattern can be observed for all classes except for BOR. The DGMD magnitude substantially increased across Europe in 2009, compared to the seven years average, probably due to the widespread reduction in milk prices in 2009 compared to 2008 (-21%) and compared to the whole seven year period (-17%). Another increase in the DGMD magnitude is observed in the BOR class in 2012 and 2013, possibly due to the overall feed cost rise in these two years compared to the seven years period (mean=+31%).

The determinants of the DGMD per dairy cow are reported in Table 4. The Wald test was highly significant (***) across all classes, indicating that the Tobit model was correctly specified. Our findings indicate that drought consistently had a significant negative effect on DGMD in BOR, CON, SOU, and UPL directly in year *t* and also a delayed effect on the year *t+1* for CON. The effect of drought is more ambiguous in NA and WA as in the current year it appears to lessen the downside risk whilst it has a negative effect in the year *t+1*. The significant effect of heat is negatively associated with DGMD across classes, with the lowest magnitude in UPL and the highest in CON (Table 4).

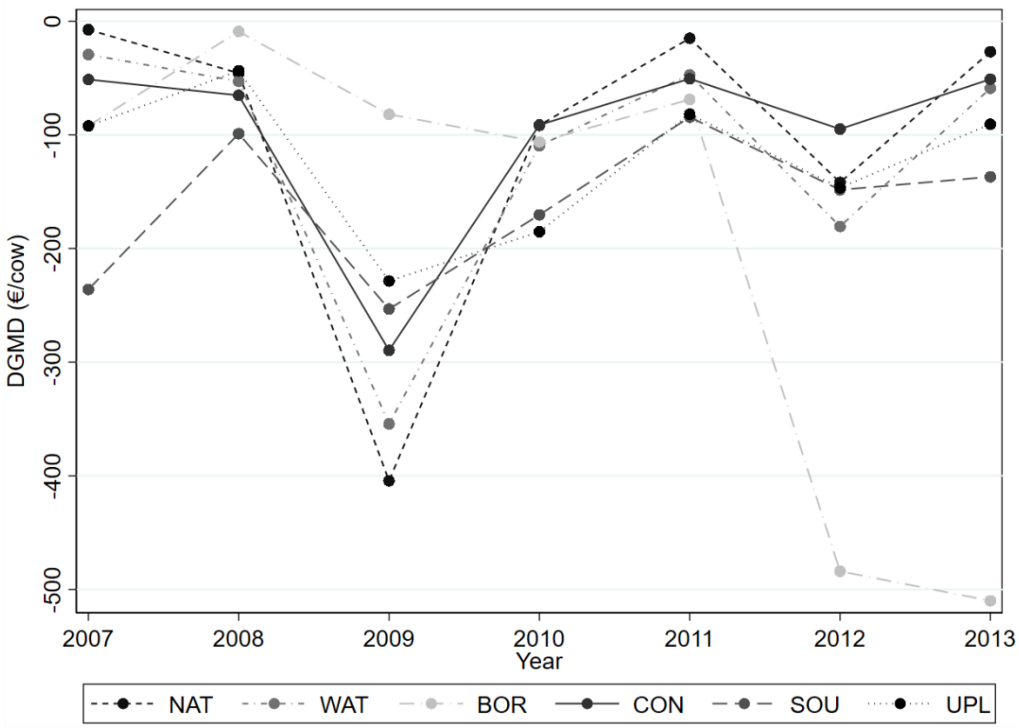

Figure 2: Mean of the downside gross margin difference (DGMD) in each climatic class from 2007 to 2013

Results for the control variables show that a higher milk price generally improves economic resilience through a reduced DGMD. In addition, a higher specialisation rate generally reduces DGMD, except for NAT and WAT that showed high specialisation rates of 73% and 72%, respectively. However, the specialisation rate was also high in BOR (79%) compared to the other classes (64 to 71%). The other variables also play a significant role on DGMD, but results are variable across classes in terms of the direction of the relationships. Organic farms are less affected than conventional ones by the economic downside risk in BOR and SOU, but in contrast, organic farms are significantly more affected in other classes.

Table 4: Influence of drought and heat stress on downside gross margin difference (DGMD) in each climatic class from 2007 to 2013

Class	NAT		WAT		BOR		CON		SOU		UPL	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
Drought	96.745***	1.958	88.679***	1.458	-51.273***	10.188	-53.421***	1.501	-129.569***	4.702	-60.705***	1.706
Lagged drought	-15.821***	1.641	-13.675***	0.794			-18.205***	0.736				
Heat	-70.497***	0.616	-20.295***	0.360	-30.457***	1.285	-133.207***	3.024	-43.429***	1.119	-16.730***	1.374
Farm size (ha)	-0.560***	0.011	0.502***	0.008	-0.422***	0.048	-0.737***	0.005	0.368***	0.024	0.332***	0.015
Specialisation (%)	-0.471***	0.047	-0.827***	0.026	14.767***	0.165	0.436***	0.017	3.696***	0.082	1.785***	0.042
Maize (%)	-2.533***	0.110	0.905***	0.022	4.151***	1.352	-1.849***	0.023	1.125***	0.053	-1.881***	0.053
Milk price (/dt)	41.358***	0.129	46.069***	0.098	5.943***	0.448	14.700***	0.042	4.883***	0.133	12.065***	0.086
Organic (yes=1)	-171.000***	10.322	-289.006***	1.879	105.477***	6.783	-67.404***	0.901	128.084***	7.048	-17.768***	1.561
Constant	-1,159.354***	4.803	-1,593.411***	3.947	-1,272.610***	22.156	-402.340***	1.534	-389.558***	6.599	-574.934***	3.961
All observations	2,289		9,478		1,589		12,306		1,799		3,423	
Number of farms	327		1,354		227		1,758		257		489	

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1; Dependent variable: DGMD [€/cow)]

The relationships between TE and DGMD are illustrated in Appendix A. Graphically, no clear link between TE and DGMD is observed across classes. In fact, the correlation between TE and DGMD is quasi-null in WAT and CON, whilst there is a slight positive correlation in the other classes, ranging from 0.20 in BOR to 0.28 in SOU.

6.1.5. Discussion and Conclusions

This study assessed the influence of drought and heat stress on the performance of a panel of EU dairy farms obtained from the FADN dataset, through measuring and estimating climate determinants of TE and DGMD. The SF and Tobit models used allowed absorption of the unobserved heterogeneity effect. The selection of the two performance indicators was justified by the absence of a clear correlation between TE and DGMD in each climatic class. This absence or weak correlation across classes indicates that highly technically efficient dairy enterprises are not necessarily economically stable and in some cases may be less resilient, as shown previously by Korhonen and Seager (2008). This finding could be due to the fact that highly technically efficient dairy enterprises operate by optimising the use of resources (e.g. grassland use) and may therefore have too limited reserve capacity to face climatic shocks.

Consistent with previous findings (Shortall and Barnes 2013, Mareth, Thomé et al. 2016, Madau, Furesi et al. 2017), this study confirms that European dairy farms are technically highly efficient and the little lower TE scores of SOU and UPL could be due to the high occurrence of drought periods in these two classes compared to the others. A significant effect of drought stress on TE was demonstrated in most of the classes. Kompas *et al.* (2004) and Chidmi *et al.* (2011) have shown similar results in Australia and North America. The delayed effect of drought observed in the NAT class could be due to a shortage of forage stock in the subsequent year, potentially causing an increase in feed costs per cow. A shortage of forage may lead to a reduced proportion of forage in the diet, which may affect production levels in absence of a high level of farm management (Beauchemin and Yang 2003). In terms of the heat stress, a significant effect was observed on TE across four out of six climatic classes. A few studies in the literature have shown comparable results in American and European

contexts (Mukherjee, Bravo-Ureta et al. 2013, Key, Sneeringer et al. 2014). The lack of a significant heat effect on TE for UPL was somehow expected as this class grouped upland farms, located above 600 m of altitude, where heat waves are less frequent and intense compared to lowland classes. In case of CON, the lack of impact of both drought and heat on TE could be due to a lower intensity level in terms of milk yield compared to the other classes, excepted for NAT.

The DGMD was also clearly affected by drought and heat stress across classes. Finger *et al.* (2018) demonstrated a negative effect of heat on the economic downside risk (on milk revenues) in German dairy farms. In this study, a surprising significant positive effect of drought was found in NAT and WAT. This finding may indicate a negative role played by excessive rainfall, as NAT and WAT are two of the three most humid classes present in the analysis, with an average daily precipitation level of 2.99 and 2.27 mm over 2007-2013, respectively. The dairy specialisation rate is positively associated to DGMD in most classes, meaning that more specialised farms often perform better in an economic downturn.

The analysis performed in this study has some limitations due to the averaging of climate data at the NUTS2 regional level to align the FADN and climate datasets, but most regions are relatively uniform. Drought and heat effects are also usually linked to large areas of high pressure, so weather patterns tend to be relatively consistent over larger areas. Another potential shortcoming of the study was the use of deflated input costs instead of input quantities that were not available in FADN. However, the inclusion of heteroskedastic variables in the 'true-fixed' effect SF model, and the inclusion of the same variables in the Tobit model allowed capturing some of the residual country heterogeneity. The FADN methodology that was used to allocate costs may not always provide a fully accurate allocation of costs to characterise the dairy enterprise.

To conclude, whilst many studies have indicated the direct effects of heat on individual cows or herds, this study has shown that the technical efficiency and economic resilience of dairy cow systems across most of Europe is negatively affected by excess heat and/or drought, even when considering the economic performance on an annual basis.

In a global warming scenario where climatic stress is expected to increase in the near future, appropriate management and innovation strategies to mitigate the effects of heat and drought are needed to limit the negative economic implications on the dairy sector. In addition to the existing cooling solutions, innovative genome-enabled selection tools should be developed in order to improve the resilience of dairy cattle to heat and associated nutritional stress in various geographical and managerial contexts (Friggens, Blanc et al. 2017). Another strategy is to encourage the development and use of more robust and frugal breeds, especially for outdoor systems that are subject to environmental perturbations (Bieber, Wallenbeck et al. 2019). Risk management strategies may also be developed, such as index insurances based on the expected effect of climatic stress on farm revenue (Vermeulen, Aggarwal et al. 2012). Finally, the agricultural policy should be tailored to help dairy farmers in adapting their systems to climate change, to reinforce their training with the support of extension advisory services and to reinforce the second pillar of the CAP to reduce intensification.

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6.1.7. References

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6.1.8. Appendix A

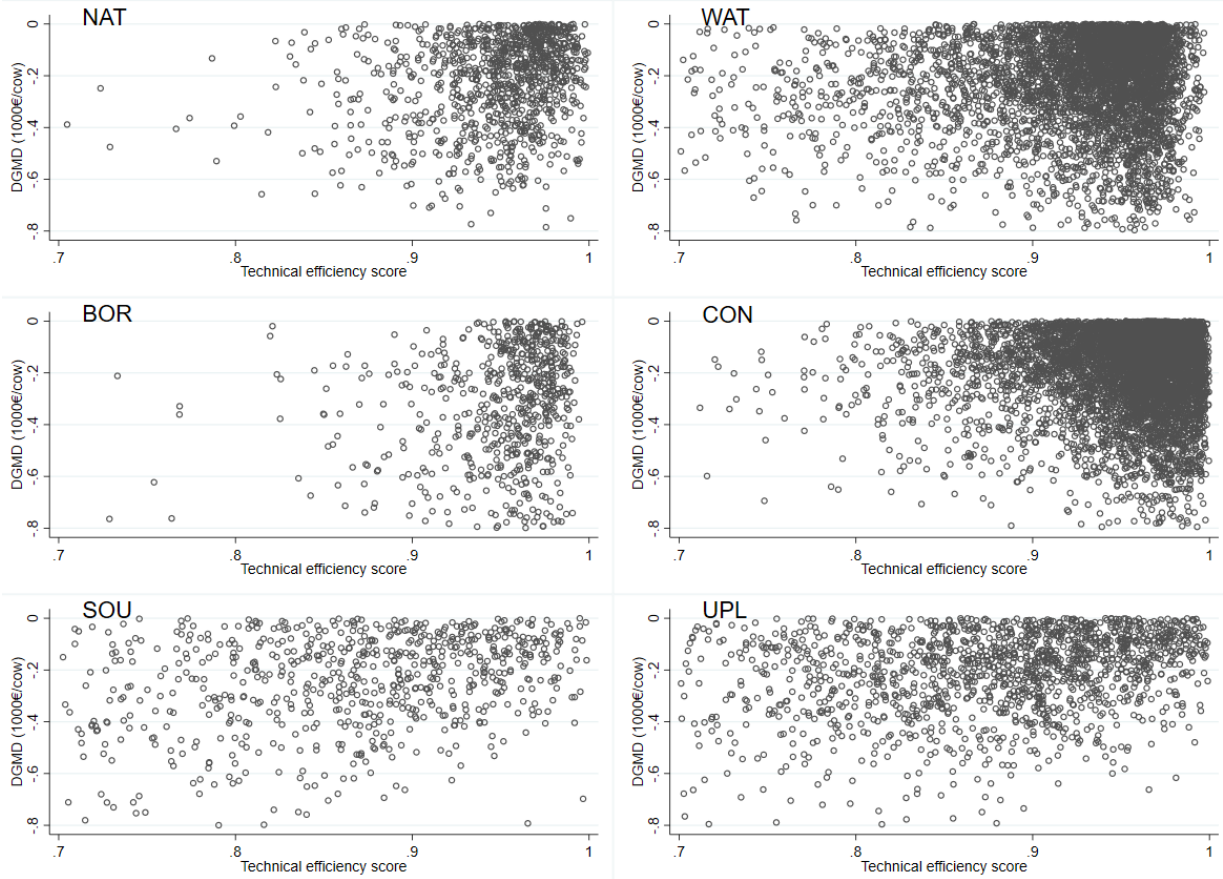

Figure 3: Relationships between technical efficiency and downside gross margin difference (DGMD) in each climatic class

6.2. Annexe 2

Climate change impacts on the productivity of EU dairy farms

6.2.1. Abstract

The majority of European dairy farms are heavily reliant on their own forage production, therefore changes in forage yields due to climate change could severely impact their production and economic performance. Utilising an FADN based database, dairy enterprise output was assessed within a range of climatic regions and across multiple system specifications to account for variation in forages and reliance on external feeds. Incorporation of FAO GAEZ potential yield data for medium and long term time periods allowed an estimation of future forage yields, obtained using a regression equation developed from baseline data. The analysis shows that whilst forage yields and therefore milk production could decline in southern European regions, more northern regions such as Boreal and North Atlantic and upland areas such as the Alps could see up to 12.5% yield increases per hectare. However, this raises questions as to the suitability of these landscapes to support higher stocking rates, so alternatively, less reliance on concentrates maybe a better option. In central and west Atlantic regions changes are expected to be less stark, but changing the current forage crop (e.g. temporary grass to alfalfa) could result in greater productivity, due to better drought tolerance. Changing forage crop could be a successful mitigation decision in areas with a yield reduction, especially as relying on an increase in external feedstuffs to replace lower yielding forages may not be possible due to increasing competition for commodities to feed a growing human population.

6.2.2. Introduction

The need for resilient production systems is clear and increasingly urgent. The majority of the EU dairy sector relies on homegrown forages as the basis of dairy cow feeding. Grass and other forages remain the cheapest and most sustainable form of cattle feed, converting human inedible feed into high quality meat and milk. Due to climatic conditions grass is more dominant in the wetter, cooler regions and maize and other forage crops such as lucerne (alfalfa) are popular in drier and warmer regions. However, with the climate predicted to continue changing during this century, what impact will climate change have upon forage production and therefore on milk production? Whilst concentrate feeds are often used to supplement forages, increases in the world population are likely to increase the competition and therefore cost and availability of such commodities. Therefore to achieve sustainable and cost effective production, high quality and yielding forage is likely to become even more critical to milk production.

To answer these questions, based on a dataset constructed in the GenTORE project using FADN and AGRI4CAST data we modelled the impact of climate change on cattle milk production in Europe. The existing baseline dataset of 130,457 observations representing 23 EU countries over the period 2004-2013 was supplemented with spatially aggregated forage yield data for current, medium and longer term time periods. Beyond assessing the expected impacts, we also modelled a simple scenario that assumed European dairy systems adapted their forages to the optimal crop in their region within the modelled timeframe, to assess this as a potential, and easy to adopt mitigation strategy.

6.2.3. Methods and data

The analysis of climate impacts on the dairy milk yield was undertaken by combining Gridded Agro-Meteorological data in Europe (AGRI4CAST) (EU, 2019a), the FAO GAEZ data in Europe (FAO, 2012), the farm accounting data available from the FADN database (EU-FADN – DG AGRI. 2019) at a NUTS2 region (e.g. French Alsace region) spatial scale (EU, 2019b).

As dairy farms can be strongly influenced by the climate context in which they operate, farms were grouped into areas representing similar climatic conditions through the use of a Latent Class Analysis model, as explained in GenTORE Deliverable 1.1 (Quièdeville et al, 2019). Six lowland classes and three upland class are evaluated in this report:

- North Atlantic (NAT)
- West Atlantic (WAT)
- Boreal (BOR)
- Central (CEN)
- Southern Central (SCEN)
- Mediterranean (MED)
- Atlantic Upland (AUPL)
- Central Upland (CUPL)
- Mediterranean Upland (MUPL)

Furthermore, since dairy farms are structurally specific, farms were also classified into different farm types based on the relative weight of the different fodder and crop areas, as explained in GenTORE deliverables 1.1 and 1.2 (Quièdeville et al 2019a, 2019b). The following detailed dairy farm types is used in this report:

- Grass (GRS)
- Grass Cropping (GRS_CRP)

- Grass Mixed (GRS_MXD)
- Grass Maize (GRS_MZE)
- MXD (Mixed)
- Mixed Cropping (MXD_CRP)
- Mixed Maize (MXD_MZE)
- Upland (UPL)

To enable an analysis of forage yields by farm type or region, Global Agro-Ecological Zones (GAEZ) agro-potential data (FAO, 2012) was utilised due to its global coverage for a range of forages. The GAEZ forage and crop yield data was downloaded from the GAEZ data portal as baseline and two future climate prediction periods: Baseline (1961-2000), 2020s (2011-2040), and 2050s (2041-2070), for the Hadley CM3 model and IPCC scenario A (the most extreme scenario). See: http://www.fao.org/nr/gaez/about-data-portal/agro-climatic-resources/en/#). A zonal statistics was applied to the GAEZ layers to aggregate the data to NUT2 region and altitude zone (0-300m, 300-600m, 600m+) with raster package in R. The result is an average yield[2] for varying forages and crops for each altitude zone in each NUTS2, for both the baseline and the future climate scenario. This data allows further analysis of the future impacts on cattle farming at both a regional scale, but also by farm type or system, which may be affected differently. As the FAO GAEZ data did not include either a composite forage yield or non-fodder yield representing the forage ration for dairy cows in Europe, a composite forage yield and composite non-fodder yield were calculated based on the share of the different farm areas available in the FADN dataset.

The baseline forage yield was calculated as follows:

$$\begin{aligned} \textit{forage yield} = {} & [(\textit{maize\_area} \times \textit{maize\_bl}) + (\textit{other\_fodder\_area} \times \textit{alfalfa\_bl}) + \\ & (\textit{tempgrs\_area} \times \textit{pasture\_grass\_bl}) + (\textit{grassPP\_RG\_area} \times \textit{pasture\_leg\_bl})] \, / \\ & (\textit{maize\_area} + \textit{other\_fodder\_area} + \textit{tempgrs\_area} + \textit{grassPP\_RG\_area}) \end{aligned} \qquad (1)$$

where *maize_bl, alfalfa_bl*, *pasture_grass_bl,* and *pasture_leg_bl* respectively represent the GAEZ yield (t/ha) baseline of fodder maize, alfalfa, pasture grass, and legume pasture; and

[2] The mean was performed on non-zero yield pixels in order to exclude non-suitable areas from average.

where *maize_area, other_fodder_area, tempgrs_area, and grassPP_RG_area* are the respective areas (ha) of fodder maize, other fodder, temporary grass, and both permanent pasture and rough grazing.

As the specific yields of other fodder area, temporary grass and both permanent pasture and rough grazing were not available in the GAEZ dataset, the yield of alfalfa, pasture grass, and legume pasture were used as proxy, respectively.

The refined dataset contained missing forage yield values due to mismatches between GAEZ and FADN data, particularly for fodder maize yield data at the altitude of 0 to 300m, 300 to 600m, and/or above 600m. The dataset was therefore refined, as indicated in equations (2), (3), (4) and (5).

When *maize_area =0* and *maize_bl=NA*, (1) is replaced by

$$forage\ yield = [(other\_fodder\_area \times alfalfa\_bl) + (tempgrs\_area \times pasture\_grass\_bl) + (grassPP\_RG\_area \times pasture\_leg\_bl)] / (other\_fodder\_area + tempgrs\_area + grassPP\_RG\_area) \quad (2)$$

When *maize_bl=NA*, (2) is replaced by

$$forage\ yield = [(maize\_area \times maize\_bl\_nuts2\_alt) + (other\_fodder\_area \times alfalfa\_bl) + (tempgrs\_area \times pasture\_grass\_bl) + (grassPP\_RG\_area \times pasture\_leg\_bl)] / (maize\_area + other\_fodder\_area + tempgrs\_area + grassPP\_RG\_area) \quad (3)$$

where *maize_bl_nuts2_alt* represents the GAEZ yield baseline of fodder maize taken at nuts2 level within each climatic class. Therefore the NUTS2 average is calculated either at the average altitude of 0 to 600m or above 600m in each nuts2. The initial *maize_bl* missing values were replaced accordingly when the fodder maize area recorded in FADN was positive.

When *maize_bl=NA*, (3) is replaced by

$$forage\ yield = [(maize\_area \times maize\_bl\_nuts1\_alt) + (other\_fodder\_area \times alfalfa\_bl) + (tempgrs\_area \times pasture\_grass\_bl) + (grassPP\_RG\_area \times pasture\_leg\_bl)] / (maize\_area + other\_fodder\_area + tempgrs\_area + grassPP\_RG\_area) \quad (4)$$

where *maize_bl_nuts1_alt* represents the GAEZ yield baseline of fodder maize taken at nuts1 level within each climatic class. The initial *maize_bl* missing values were replaced accordingly when the fodder maize area recorded in FADN was positive.

When *maize_bl=NA*, (4) is replaced by

$$forage\ yield = [(maize\_area \times maize\_bl\_nuts2) + (other\_fodder\_area \times alfalfa\_bl) + (tempgrs\_area \times pasture\_grass\_bl) + (grassPP\_RG\_area \times pasture\_leg\_bl)] / (maize\_area + other\_fodder\_area + tempgrs\_area + grassPP\_RG\_area) \quad (5)$$

where *maize_bl_nuts2* represents the GAEZ baseline yield of fodder maize taken at nuts2 level, with no differentiation in terms of altitude level. The initial *maize_bl* missing values were replaced accordingly when the fodder maize area recorded in FADN was positive.

The same data processing as for the baseline was done to compute the forage yield for the mid-term scenario (2011-2040) and the long-term scenario (2041-2070).

After this data processing, forage yield for 3,858 FADN observations were still missing and could not be replaced; therefore these observations were excluded from the analysis. The refined dataset contained 138,103 observations.

As for the composite yield of non-fodder crops used for feed, the equivalent cost per ha of forage area was used as a proxy for the baseline in order to align with the per forage hectare unit. The non-fodder proxy for the mid-term and long-term scenario was calculated based on the proportional change of a composite non-fodder yield from the mid-term to the long-term GAEZ scenario. This composite non-fodder yield was based on the yield of barley, wheat and pea. The equations (6) to (11) present the procedure:

$$coeff\_20\_barley = (barley\_20 / barley\_bl) \quad (6)$$

where *coeff_20_barley* is the ratio of the mid-term barley yield *barley_20* to the barley yield baseline *barley_bl*.

$$coeff\_50\_barley = (barley\_50 / barley\_bl) \quad (7)$$

where *coeff_50_barley* is the ratio of the long-term barley yield *barley_50* to the barley yield baseline *barley_bl*.

The same calculation as for barley was undertaken to compute the ratio of change in wheat and pea from the mid-term to the long-term GAEZ scenario. The composite non-fodder yield for the mid-term and long-term scenarios were then calculated as follows:

$$x_1 = mean[(ce\_nfodder\_ha \times coeff\_20\_barley) + (ce\_nfodder\_ha \times coeff\_20\_wheat) + (ce\_nfodder\_ha \times coeff\_20\_pea)] \quad (8)$$

where $\bar{x}_1$ is the average composite yield of barley, wheat, and dry pea in the mid-term scenario ; and where *coeff_20_wheat* is the ratio of the mid-term wheat yield to the wheat yield baseline, and *coeff_20_pea* is the ratio of the mid-term pea yield to the pea yield baseline.

$$x_2 = mean[(ce\_nfodder\_ha \times coeff\_50\_barley) + (ce\_nfodder\_ha \times coeff\_50\_wheat) + (ce\_nfodder\_ha \times coeff\_50\_pea)] \quad (9)$$

where $\bar{x}_2$ is the average composite yield of barley, wheat, and dry pea in the long-term scenario ; and where *coeff_50_wheat* is the ratio of the long-term wheat yield to the wheat yield baseline, and *coeff_50_pea* is the ratio of the mid-term pea yield to the pea yield baseline.

As the yield of dry pea was not available in all NUTS2 regions, further differentiated by the altitude level, the composite non-fodder yield for the mid-term and long-term scenario was revised, as indicated in equations (10) and (11).

When *coeff_20_pea=NA* and/or *pea_bl=NA*, (8) is replaced by

$$x_1 = mean[(ce\_nfodder\_ha \times coeff\_20\_barley) + (ce\_nfodder\_ha \times coeff\_20\_wheat)] \quad (10)$$

where *pea_bl* is the baseline yield of dry pea.

When *coeff_50_pea=NA* and/or *pea_bl=NA*, (9) is replaced by

$$x_2 = mean[(ce\_nfodder\_ha \times coeff\_50\_barley) + (ce\_nfodder\_ha \times coeff\_50\_wheat)] \quad (11)$$

Since the entire analysis was undertaken on a per forage hectare basis, and to reduce possible biases in results, the intensive farms, i.e. with a stocking density [grazing livestock unit (GLU)/ha] >5, were excluded from the analysis. Due to natural forage yield limitations, farms with a very high stocking rate would be very reliant on external feeds and forage areas may be little more than feedlot areas so were excluded. The dataset was therefore further reduced to 130,457 observations representing 23 EU countries over the period 2004-2013.

Table 1 and

Table 2 indicate the main descriptive statistics for production, structure and economic variables by dairy farm type and climatic classes, respectively.

Table 1 Production, structure, and economic characterization of each dairy farm type from 2004 to 2013

Farm type	Value	Milk yield /ha (kg)	UAA (ha)	Dairy cow (#)	Spec (%)	GLU/ ha	Crop area (%)	Maize area (%)	PP&RG* area (%)	TG** area (%)	Other fodder area (%)	Ext. feed (%)	Forage cost/ ha (€)	Home non-fodder cost/ ha (€)	Conc cost/ ha (€)	Ext. fodder cost/ ha (€)	Margin /ha (€)	n
GRS	mean	8,402	10	58	74	1.7	3	2	70	24	1	53	115	253	740	101	1,188	27,241
	p50	7,341	50	43	76	1.6	0	0	86	0	0	56	90	147	497	12	941	
GRS_CRP	mean	6,808	119	52	64	1.4	30	5	39	25	1	32	129	361	394	31	958	19,918
	p50	6,057	60	31	64	1.4	29	0	51	9	0	32	115	262	247	0	803	
GRS_MXD	mean	9,560	82	64	72	1.9	9	15	55	13	9	48	183	286	670	85	1,440	8,367
	p50	8,573	54	44	73	1.8	9	17	62	0	3	50	173	144	494	4	1,266	
GRS_MZE	mean	12,623	66	81	77	2.3	5	33	43	18	1	55	271	348	962	129	1,795	5,582
	p50	11,750	51	59	80	2.2	0	31	54	0	0	57	264	100	808	23	1,567	
MXD	mean	9,756	75	54	68	2.0	23	10	18	3	47	39	188	472	664	72	1,442	5,884
	p50	8,790	38	32	69	1.9	24	10	13	0	42	39	169	289	413	0	1,180	
MXD_CRP	mean	10,048	206	81	55	2.1	53	13	22	7	5	33	223	489	528	52	1,271	38,981
	p50	9,175	61	33	54	2.0	53	12	23	0	0	34	209	382	402	0	1,120	
MXD_MZE	mean	14,163	83	88	72	2.6	17	45	19	11	9	50	332	601	1,124	121	1,685	9,180
	p50	13,200	52	56	74	2.4	18	39	16	0	0	51	304	265	911	19	1,528	
UPL	mean	6,626	90	39	64	1.4	7	4	63	17	9	50	66	349	572	77	1,078	15,304
	p50	5,408	34	25	65	1.3	0	0	76	0	0	52	37	161	329	6	832	
Total																		**130,457**

* Permanent pasture and rough grazing

** Temporary grass

Table 2 Production, structure, and economic characterization of dairy farms within each climatic class from 2004 to 2013

Climatic region	Value	Milk yield /ha (kg)	UAA (ha)	Dairy cow (#)	Spec (%)	GLU/ ha	Crop area (%)	Maize area (%)	PP&RG area (%)	TG area (%)	Other fodder area (%)	Ext. feed (%)	Forage cost/ ha (€)	Home non-fodder cost/ ha (€)	Conc cost/ ha (€)	Ext. fodder cost/ ha (€)	Margin /ha (€)	n
NAT	mean	9,593	80	85	74	2.1	3	1	80	14	1	53	224	264	695	57	1,082	6,902
	p50	9,044	63	67	76	2.0	0	0	88	0	0	53	212	228	546	15	1,006	
WAT	mean	11,771	87	74	70	2.2	19	20	45	12	4	53	240	301	919	121	1,642	36,743
	p50	10,721	70	56	71	2.0	14	18	43	0	0	54	235	105	731	17	1,449	
BOR	mean	8,574	67	36	79	1.3	29	0	2	67	2	48	183	364	813	16	1,164	3,842
	p50	8,090	56	27	82	1.3	31	0	0	65	0	48	178	257	736	0	1,065	
CEN	mean	7,766	165	65	61	1.7	37	10	36	12	6	32	149	377	363	33	1,036	57,331
	p50	6,980	43	26	60	1.6	37	8	33	0	0	31	133	309	253	0	867	
SCEN	mean	11,042	129	74	64	2.2	22	14	29	27	8	42	197	949	1026	152	1,392	7,418
	p50	9,068	36	35	64	2.0	16	9	16	11	0	41	161	812	607	0	872	
MED	mean	12,072	51	52	66	2.4	15	8	18	30	29	50	175	968	1,264	156	1,723	2,917
	p50	10,186	30	35	67	2.3	0	0	0	0	0	51	120	787	858	0	1,161	
AUPL	mean	8,307	482	191	70	1.5	16	4	76	0	3	49	110	286	511	41	1,258	67
	p50	6,859	79	50	71	1.3	11	0	86	0	0	52	120	115	455	21	1,272	
CUPL	mean	5,564	101	39	63	1.3	7	3	69	13	8	49	55	279	432	65	923	12,070
	p50	4,859	35	24	62	1.2	0	0	85	0	0	51	26	128	286	10	769	
MUPL	mean	10,638	38	36	70	2.0	11	9	36	33	11	54	108	621	1,109	123	1,661	3,167
	p50	8,550	28	29	72	1.8	1	0	22	15	0	58	82	509	781	0	1,189	
Total																		**130,457**

6.2.3.1. Model

The milk production forecast analysis in EU dairy system was undertaken on a per forage hectare basis to directly take account of the influence of the stocking density on dairy farm system performance. A high per cow performance may be due to a low stocking rate, and land area is usually the main limiting factor of farms in Europe, so the use of per hectare values seemed the most appropriate.

A linear regression was preliminary performed to find the causal relationships between the milk yield and relevant independent variables. These causal relationships were then used to predict the dairy milk production per forage hectare in the mid-term and long-term GAEZ scenarios.

6.2.3.2. Baseline model

The annual production of milk (kg) per forage hectare was used as a dependent variable. The home-grown forage input was expressed in milk quantity using the calculated composite forage yield based on GAEZ data. The other input variables were expressed in constant monetary values as information on their quantity was not available from FADN. The price indices of the means of agricultural production provided by Eurostat (2019 and 2018) was used to deflate non-fodder costs, whilst the other economic variables were adjusted by the Harmonised Index of Consumer Prices (HICP). Inputs were also expressed per forage hectare and comprised the forage yield (t/ha), the home-grown non-fodder costs, the purchased concentrate costs, the purchased fodder costs, the maintenance costs (machinery, cars, building, and land improvement) and other costs (herd replacement, contractual work, and veterinary services).

The model was parameterised as follows:

$$PROD = forage\_bl*a + non\_fodder\_bl*b + ce\_conc\_ha*c + ce\_coarse\_ha*d + ce\_mach\_ha*e + ce\_oth\_ha*f + i.cl*g + \text{constant} \quad (12)$$

where PROD is the production of milk (kg) per forage hectare, *i.class* means that the climatic class *cl* is included as a fixed effect to account for major differences in the “technology” across different European regions; and

where *forage_bl* is the forage yield, *non_fodder_bl* is the home-grown non-fodder costs, *ce_conc_ha* is the purchased concentrate costs, *ce_coarse_ha* is the purchased fodder costs, *ce_mach_ha* is the maintenance costs, and *ce_oth_ha* are the other costs.

The potential effect of heat and drought stress on milk production over time and in each NUTS2 region was considered neutral at farm level, meaning that the average milk production value over the ten years period was considered as balanced by the relative weight of good and poor years. The effect of climate change on milk production will be considered through the change it implies on home-grown forage and non-fodder productivity. Although climate change could also affect animal productivity directly, this study was more focussed on forage productivity, therefore, potential climate effect on animal productivity was be excluded from the production forecast estimation.

6.2.3.3. Prediction model

The production forecast is based on the causal linear relationships found in the regression model constructed to predict the milk production level from the baseline dataset. The same

model is used for the forecast analysis, using the predicted coefficients. The expected forage yield and home-grown non-fodder costs (proxy variable) in the mid-term and long-term scenarios are used to substitute the corresponding baseline values and to predict the milk production per forage hectare in the mid and long-term, respectively. All the other values for the other variables remain identical.

The forage yield calculation was “nested” into the prediction equation to allow hypothesis on changes in the relative share of fodder areas on the farm. In effect, changing the forage crop rotation is one possible way to adapt to climatic change.

6.2.3.4. Predicted stocking density and predicted margin calculation

The assumption was made of a fixed quantity of feed per dairy cow in the different scenarios. This implies that any decrease or increase in the milk yield production per forage hectare affects the stocking density to the same proportion.

The predicted margin per hectare of forage area was calculated through the assumption that all the other factors remain constant. The margin (in constant €) was calculated as the difference between the revenue (milk yield*price) and the forage, feed, machinery, hired labour and other costs (herd replacement, contractual work, and veterinary services). Since the forage yield is expected to change in the future, the forage costs are also likely to change. However, they may not increase or decrease to the same proportion due to the presence of cost that are usually not fully proportional to the yield such as the seeds and pesticides costs. The assumption was made that any increase of 1% (and vice versa) in the yield will only increase the forage cost (per forage hectare) by 0.25% for the pastures and other fodder crops, and by 0.5% for the fodder maize and non-fodder crops. A higher cost incurrence for maize and other forage crops was assumed due to higher costs for seed and regular cultivation.

6.2.3.5. External feed dependency

The hypothesis was made that farms that heavily rely on external feed may be less negatively affected by climatic change since the relative climate impact on their own forage production is theoretically less important as for more independent dairy farms. This hypothesis was tested by defining quartiles of external feed dependency (%) and analysing the relationship between the level of dependency and the predicted milk yield in the mid and long-term scenarios. The percentage of external feed dependency was calculated as the ratio of the purchased feed to the home grown forage costs. The forage costs included here both the direct costs (based on fertilisers, pesticides and seeds costs) and the more indirect machinery costs.

6.2.3.6. Yield maximisation

As European dairy farmers may adapt to climate change by changing their rotation, a simple linear programming was performed to test the hypothesis of forage yield maximisation in the mid and long-term scenarios. The constraint was set that the area (%) of permanent pastures & rough grazing could not decrease as these areas may not be difficult to cultivate, the CAP restricts cultivation of permanent grassland and as usually an area of grassland is needed for fall back grazing for dairy cows. The other fodder areas, i.e. the temporary grass, fodder maize and other fodder areas were assumed to be completely freely cultivable (though in reality there may be unforeseen restrictions).

6.2.4. Results

6.2.4.1. Linear regression output

Table 3 indicates the causal relationships between the milk yield and the different input variables in each farm type across Europe..

Table 3 Milk production determinants in each dairy farm type

Variables \ Farm type /	GRS	GRS_CRP	GRS_MXD	GRS_MZE	MXD	MXD_CRP	MXD_MZE	UPL
[Forage (t/ha)*100]	1.081***	2.905***	2.233***	1.183***	6.764***	5.665***	5.960***	2.610***
Non-fodder (€/ha)	1.211***	1.437***	0.680***	0.467***	2.103***	2.293***	1.012***	2.040***
Concentrates (€/ha)	3.437***	3.789***	3.979***	4.123***	3.393***	4.116***	4.039***	3.189***
Ext. fodder (€/ha)	3.400***	1.892***	4.234***	4.166***	2.984***	4.011***	3.481***	0.907***
Machinery (€/ha)	4.533***	4.790***	4.728***	3.603***	6.656***	5.162***	4.324***	7.098***
Other costs (€/ha)	4.645***	3.385***	3.913***	3.405***	3.784***	2.874***	3.593***	5.108***
1.NAT				*Reference*				
2.WAT	-419.6***	-1,255***	-1,247***	-32.42	597.2	-2,235***	-695.7	
3.BOR	-3,410***	-2,866***	-3,981***	*NA*	-768.5	-3,844***	*NA*	
4.CEN	-1,797***	-1,885***	-1,279***	-53.47	791.1	-1,651***	288.5	
5.SCEN	-1,501***	-2,954***	-2,347***	-567.8	-748.6	-5,142***	-2,381**	
6.MED	750.7***	-474.7***	-2,396***	2,310***	-299.5	-1,081**	-1,942*	
7.AUPL								*Reference*
8.CUPL								-1,233***
9.MUPL								792.9**
Constant	2,959***	2,836***	3,221***	4,082***	-2,347**	2,037***	580.1	1,056***
n	27,241	19,918	8,367	5,582	5,884	38,981	9,180	15,304
R^2	**0.799**	**0.701**	**0.790**	**0.710**	**0.695**	**0.626**	**0.709**	**0.751**

*Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1; Dependent variable: Milk production (kg/ha)*

The input independent variables are all highly significant across dairy farm types, and the r-squared is also high across classes, suggesting that the causal model is a good representation of the reality. We observe that forage yield has the highest impact on milk yield in the mixed systems, whilst the external coarse fodder cost has the lowest impact on milk yield in the grass cropping and upland systems.

6.2.4.2. Predicted milk yield in the mid and long-term in Europe by farm types and climatic classes

Figure 4 indicates the predicted milk yield in the baseline, mid-term and long-term scenarios for each farm type across Europe. Overall, the changes from the baseline are not big, though we clearly observe a slight increase in milk yield in the three mixed systems and in upland regions.

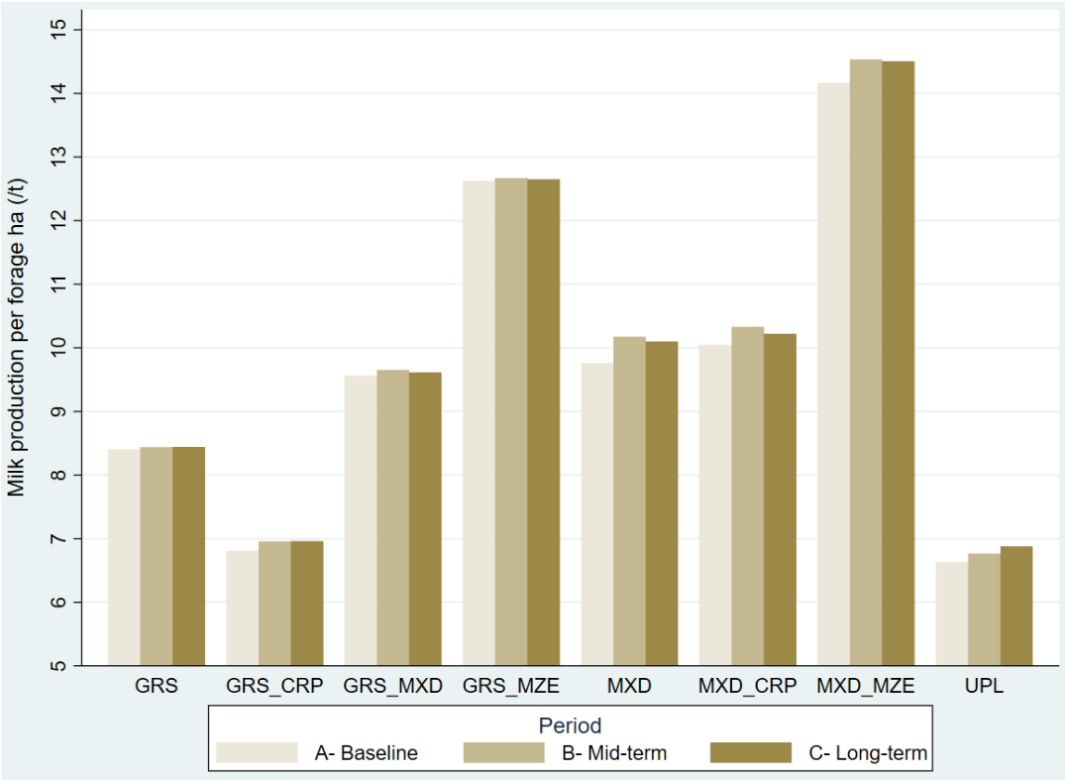

Figure 4 Predicted milk yield in each dairy farm type

This slight increase in milk yield in the three mixed systems and in upland regions is associated with a slight increase in the predicted stocking density and margin (€/ha) from the baseline to the mid-term period as indicated in Table 4. However, the economic performance tend to decline from the mid-term to the long-term horizon in these farm systems.

Table 4 Predicted milk yield, stocking density, and margin (€/ha) in each dairy farm type

Period		Baseline			Mid-term			Long-term			n
Farm type	Value	Milk yield /ha (kg)	GLU/ ha	Margin /ha (€)	Milk yield /ha (kg)	GLU/ ha	Margin /ha (€)	Milk yield /ha (kg)	GLU/ ha	Margin /ha (€)	
GRS	mean	8,402	1.77	1,229	8,435	1.77	1,235	8,442	1.77	1,233	27,241
	p50	7,472	1.66	1,071	7,512	1.66	1,079	7,518	1.66	1,077	
GRS_CRP	mean	6,808	1.50	1,011	6,955	1.53	1,053	6,958	1.52	1,049	19,918
	p50	6,020	1.37	908	6,109	1.40	952	6,057	1.38	940	
GRS_MXD	mean	9,560	1.92	1,533	9,649	1.94	1,555	9,612	1.93	1,541	8,367
	p50	8,360	1.79	1,420	8,453	1.81	1,434	8,396	1.80	1,417	
GRS_MZE	mean	12,623	2.39	1,939	12,669	2.40	1,937	12,647	2.39	1,924	5,582
	p50	11,658	2.22	1,846	11,724	2.23	1,841	11,717	2.23	1,828	
MXD	mean	9,756	2.06	1,547	10,171	2.15	1,669	10,097	2.13	1,644	5,884
	p50	8,691	1.90	1,374	9,122	2.01	1,507	9,010	2.00	1,472	
MXD_CRP	mean	10,048	2.16	1,417	10,327	2.21	1,490	10,219	2.19	1,452	38,981
	p50	9,218	2.02	1,334	9,451	2.08	1,406	9,317	2.04	1,364	
MXD_MZE	mean	14,163	2.62	1,866	14,534	2.69	1,956	14,505	2.68	1,934	9,180
	p50	12,995	2.40	1,834	13,519	2.50	1,928	13,485	2.50	1,899	
UPL	mean	6,626	1.54	1,148	6,764	1.57	1,184	6,876	1.60	1,221	15,304
	p50	5,476	1.29	936	5,637	1.33	980	5,769	1.36	1,028	

Figure 5 indicates the predicted milk yield in the baseline, mid-term and long-term scenarios for each climatic class. We clearly observe an increase in milk yield production in the BOR climatic class as well as in the coolest upland regions (AUPL & CUPL). Contrariwise, the milk yield clearly decrease in the SCEN and MUPL climatic classes, and also in the MED class to a lesser extent.

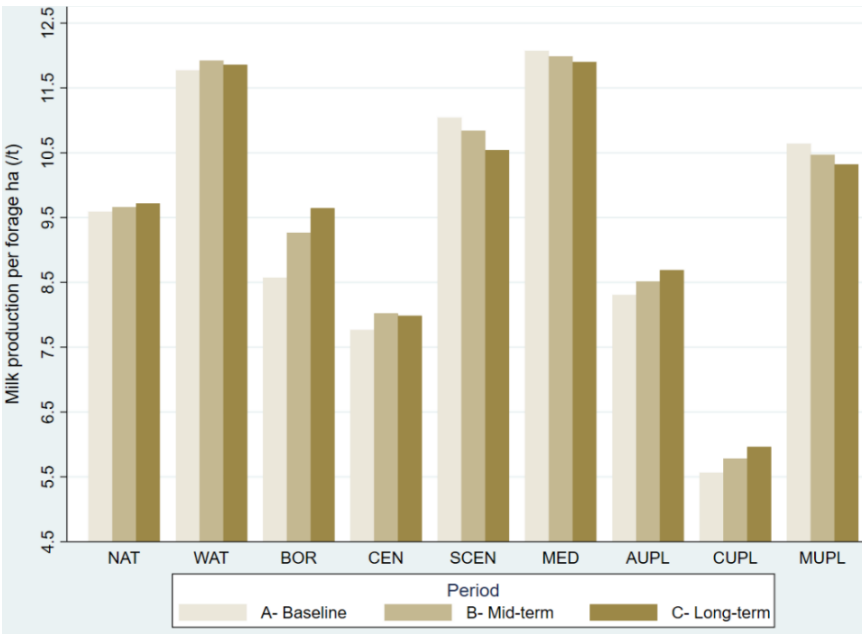

Figure 5 Predicted milk yield in each climatic class

Table 5 indicates an associated significant increase in the predicted margin in the BOR class from the baseline to the long-term scenario (≈ +400€/ha).

Table 5 Predicted milk yield, stocking density, and margin (€/ha) in each climatic class

Period		Baseline			Mid-term			Long-term			n
Climatic class	**Value**	**Milk yield /ha (kg)**	**GLU/ ha**	**Margin /ha (€)**	**Milk yield /ha (kg)**	**GLU/ ha**	**Margin /ha (€)**	**Milk yield /ha (kg)**	**GLU/ ha**	**Margin /ha (€)**	
NAT	mean	9,593	2.11	1,140	9,662	2.12	1,157	9,719	2.14	1,168	6,902
	p50	8,740	2.01	1,082	8,793	2.02	1,097	8,848	2.04	1,106	
WAT	mean	11,771	2.23	1,770	11,922	2.26	1,798	11,856	2.24	1,769	36,743
	p50	10,637	2.06	1,649	10,706	2.09	1,662	10,574	2.07	1,620	
BOR	mean	8,574	1.36	1,186	9,267	1.47	1,433	9,644	1.53	1,561	3,842
	p50	7,972	1.26	1,082	8,610	1.36	1,312	8,940	1.42	1,432	
CEN	mean	7,766	1.76	1,128	8,022	1.82	1,194	7,986	1.80	1,179	57,331
	p50	7,353	1.67	1,032	7,597	1.73	1,093	7,521	1.71	1,070	
SCEN	mean	11,042	2.34	1,513	10,839	2.29	1,473	10,540	2.23	1,387	7,418
	p50	9,036	2.05	1,112	8,873	2.01	1,075	8,628	1.96	1,004	
MED	mean	12,072	2.60	1,848	11,988	2.58	1,827	11,899	2.55	1,792	2,917
	p50	10,025	2.28	1,603	9,899	2.26	1,586	9,835	2.24	1,557	
AUPL	mean	8,307	1.54	1,346	8,516	1.58	1,403	8,691	1.62	1,449	67
	p50	7,969	1.49	1,237	8,136	1.52	1,313	8,119	1.55	1,333	
CUPL	mean	5,564	1.37	998	5,783	1.43	1,055	5,963	1.47	1,114	12,070
	p50	4,844	1.19	839	5,069	1.24	889	5,242	1.27	946	
MUPL	mean	10,638	2.16	1,716	10,468	2.12	1,671	10,320	2.09	1,625	3,167
	p50	8,906	1.92	1,482	8,754	1.88	1,442	8,594	1.85	1,394	

Figure 6 indicates the predicted milk yield and associated changes in specific farm systems and within different. climatic classes (See **Table 6** and **Table 7** in the appendix). The BOR climatic class remains quite positively affected, particularly concerning the mixed cropping system. The situation is very stable in the other regions, apart from the SCEN climatic class where the milk production tend to decline a bit over time.

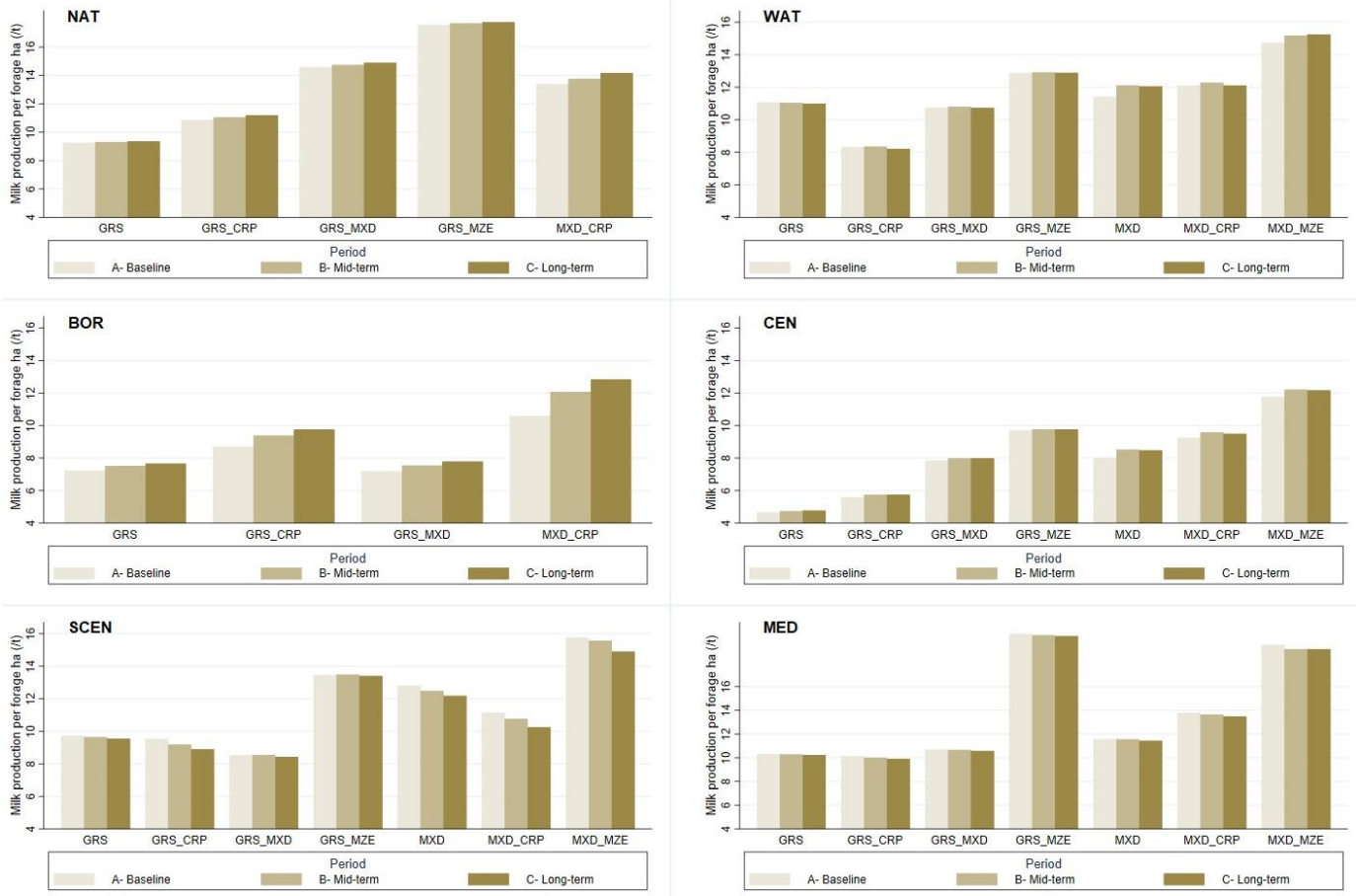

Figure 6 Predicted milk yield in each dairy farm type within each climatic class in lowland European regions

6.2.4.3. Effect of external feed dependency on milk yield predictions

The effect of external dependency on milk production was analysed by quartile of dependency level (%). Figure 7 indicates the results for each of the dairy farm type (See Table 8 in the appendix). Here again, differences between the different scenarios are more visible in the most mixed systems, where we can observe that the most dependent system on external feed then to be very slightly more stable in terms of predicted milk yields.

Figure 8 indicates the results for each of the climatic classes in the lowland and upland regions (See **Table 9** in the appendix). The most dependent farms in the BOR class are clearly more stable in terms of yield production, however, they are missing the opportunity to actually increase their milk production. By contrast, we observe in the SCEN climatic class that the most dependent farms on external feed are slightly more resilience to climate change as the milk production declines less in the mid-term and long-term scenarios compared to more independent farms.

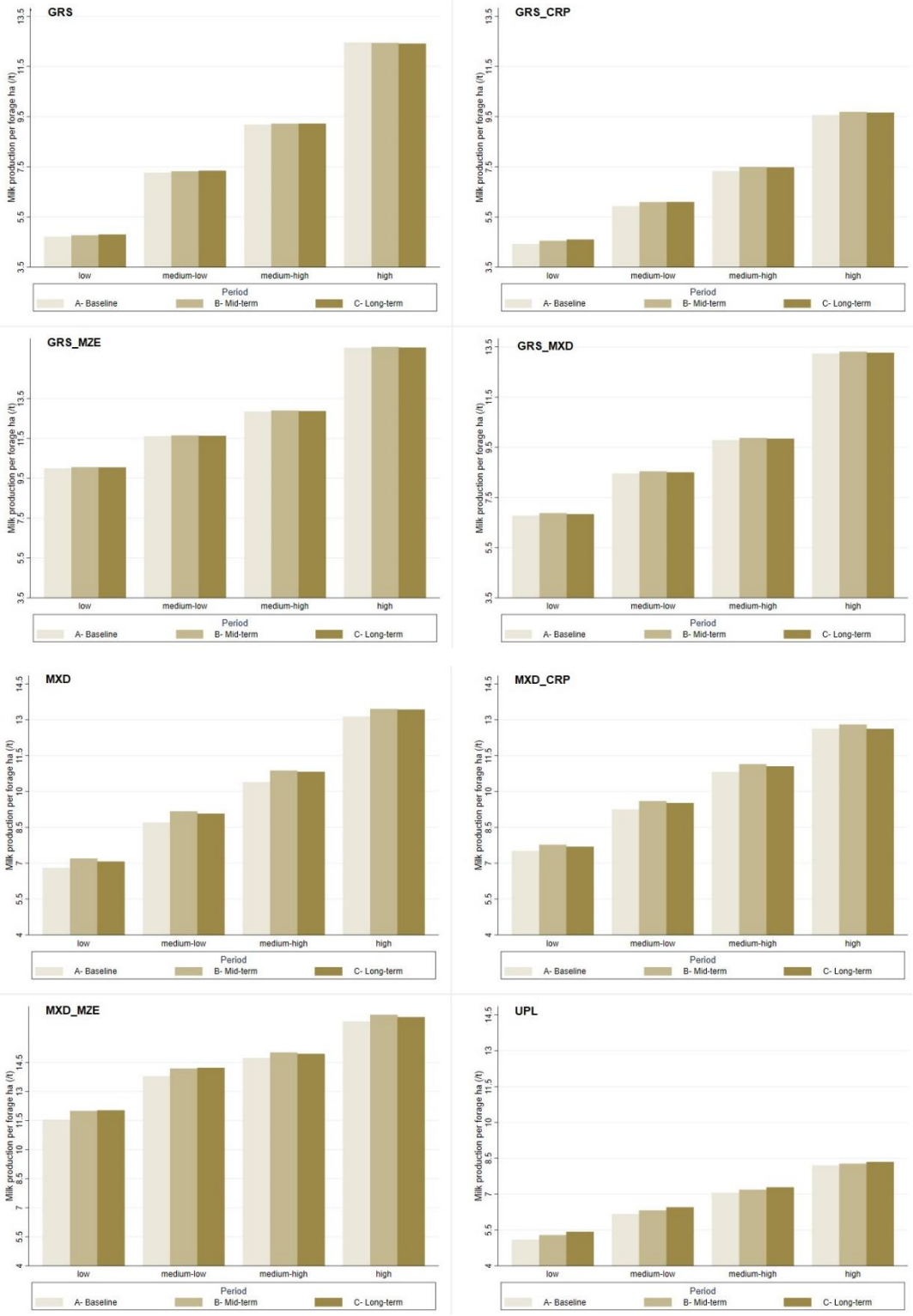

Figure 7 Effect of external feed dependency on milk yield predictions in the dairy grass, grass cropping, grass maize, grass mixed, mixed, mixed cropping, mixed maize and upland systems across Europe systems across Europe

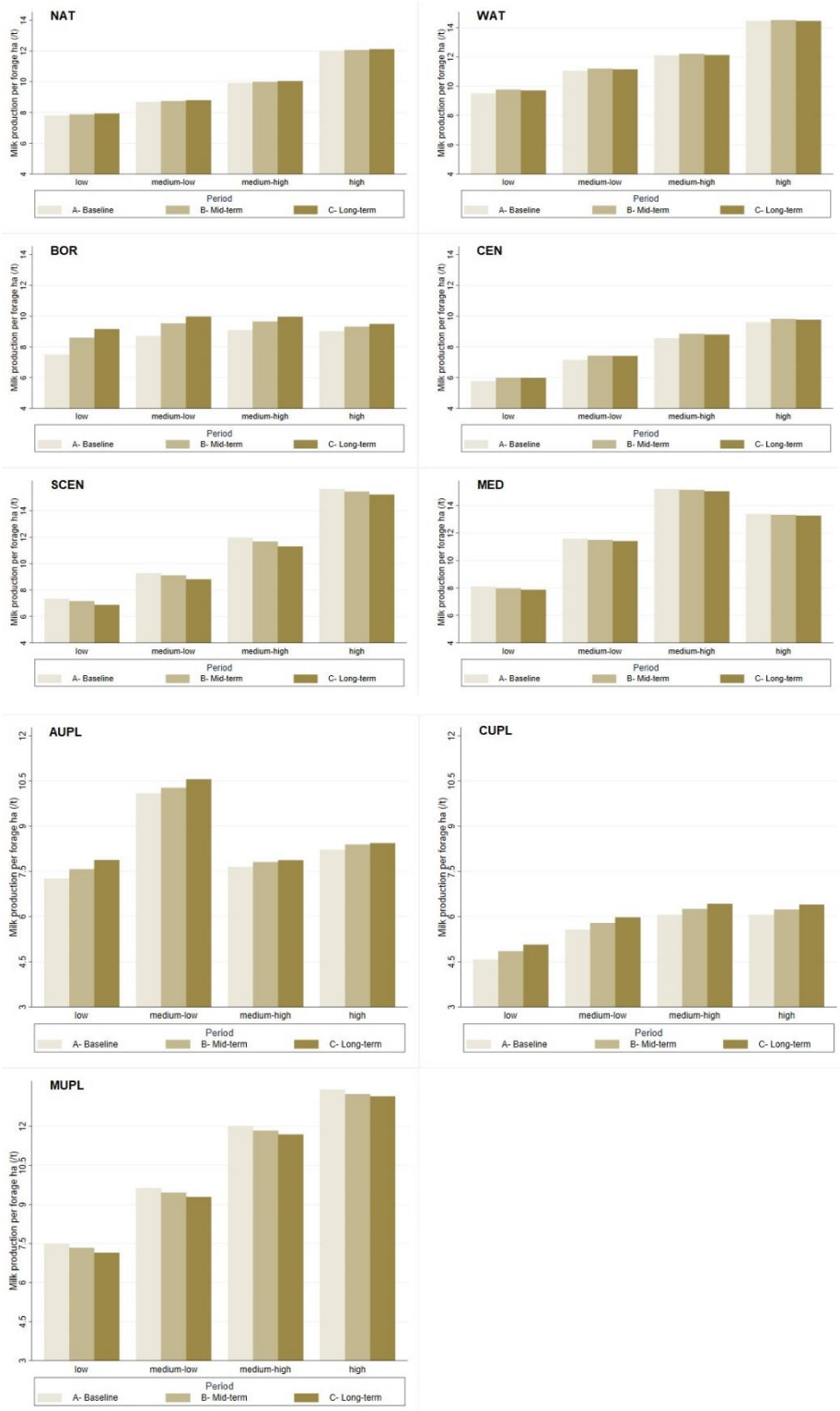

Figure 8 Regional effect of external feed dependency on milk yield predictions

The effects of dependancy on external feed (split by quartiles) for each farm type and region was assessed and are presented in the appendix (Table 10 to

Table 12) present the results on external feed dependency for each farm type with each of the lowland climatic classes.

For most farm types and regions the impacts are similar, for example, In the BOR climatic class, the mixed cropping and grass cropping are the most dependent farms on external feed, and are also those for which the yield gap between the baseline and the mid-term and long-scenarios is proportionally the less important.

6.2.4.4. Predicted milk yield in the optimisation scenario

The hypothesis of forage yield maximisation was made in order to see whether and how could EU dairy farmers could adapt to climate change. Figure 9 shows the difference in milk yield between the non-optimisation and optimisation scenario over time (over the mid-term and long-term periods) in each farm type across Europe (see Table 13 in the appendix). The mixed systems seem to be more positively affected by the optimisation scenario compared to the other systems. The graph show that the optimisation does not mitigate a reduced project milk yield but rather improves the situation of all scenarios, even the baseline, meaning that the baseline situation itself is not always the most optimal one from a productivity viewpoint.

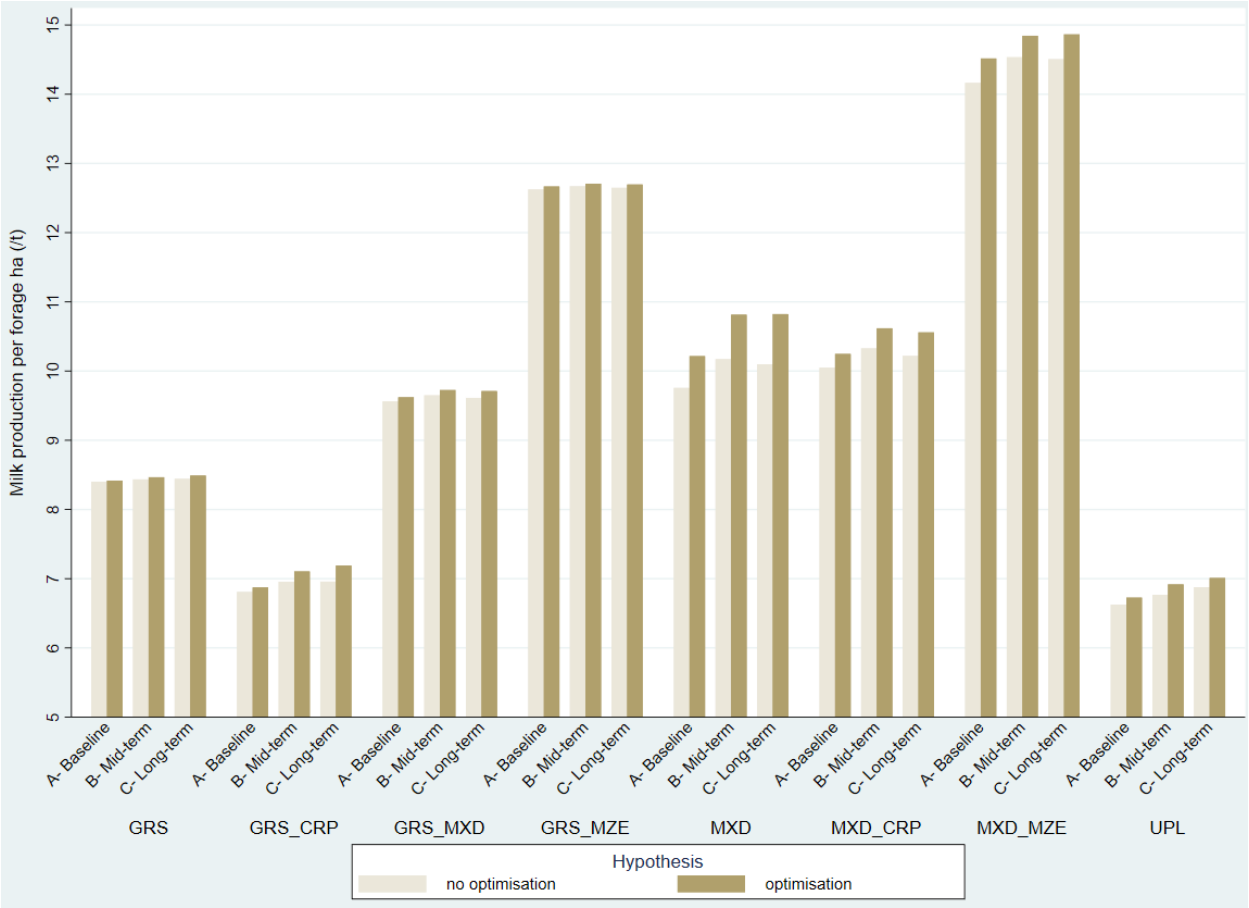

Figure 9 Predicted milk yield in each dairy farm type, with and without farm adaptation

The Figure 10 shows the difference in milk yield between the non-optimisation and optimisation scenario over time (over the mid-term and long-term periods) in each climatic class in Europe

(see Table 14 in the appendix). There is no clear pattern in terms of the predicted evolution of milk yield, but we observe that the CEN, SCEN, MED, and MUPL would profit the most from optimising their systems in the different scenarios incl. the baseline.

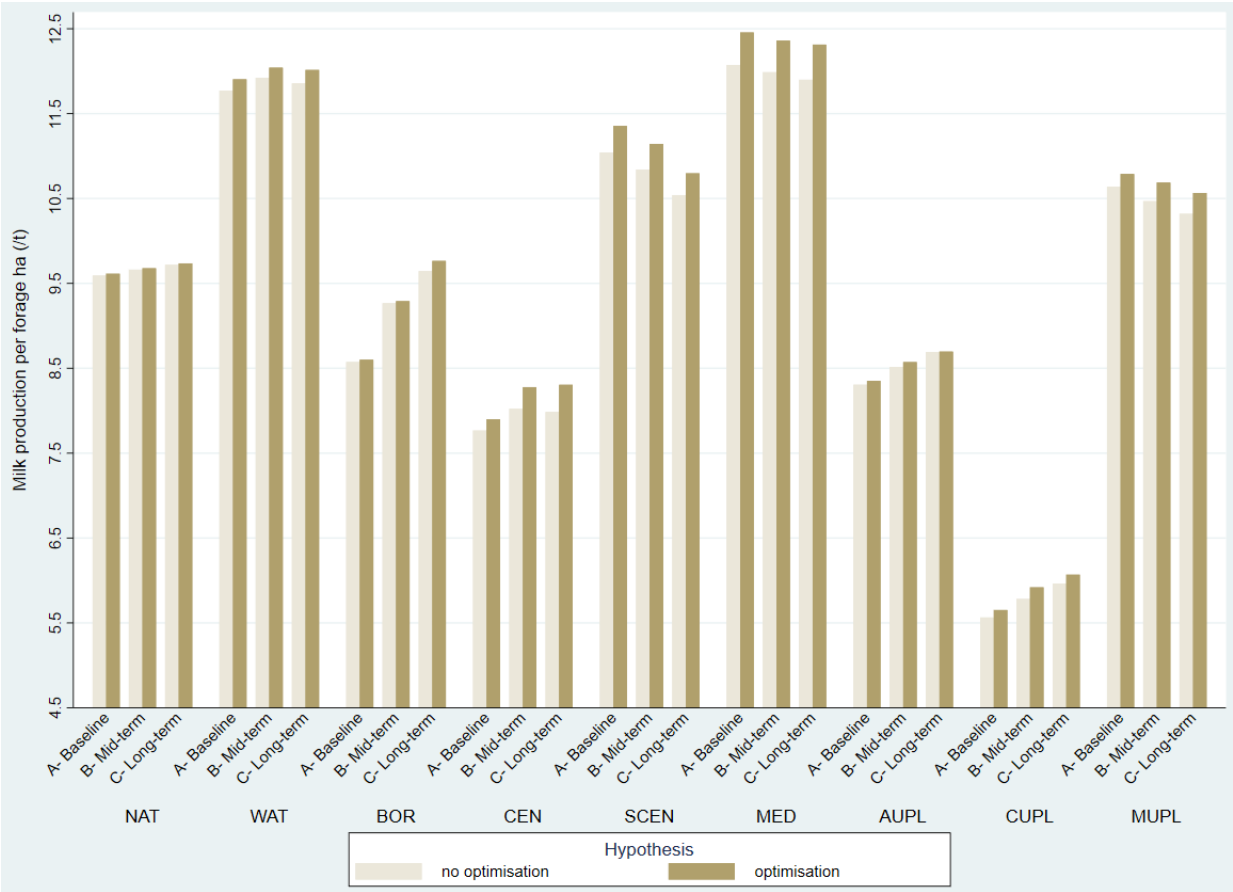

Figure 10 Predicted milk yield in each climatic class, with and without farm adaptation

The subsequent Figure 11 and Figure 12 present the results on milk yield optimisation for each farm type within each of the lowland climatic classes, respectively. Full data tables are shown in the appendix (Table 15 and Table 16).

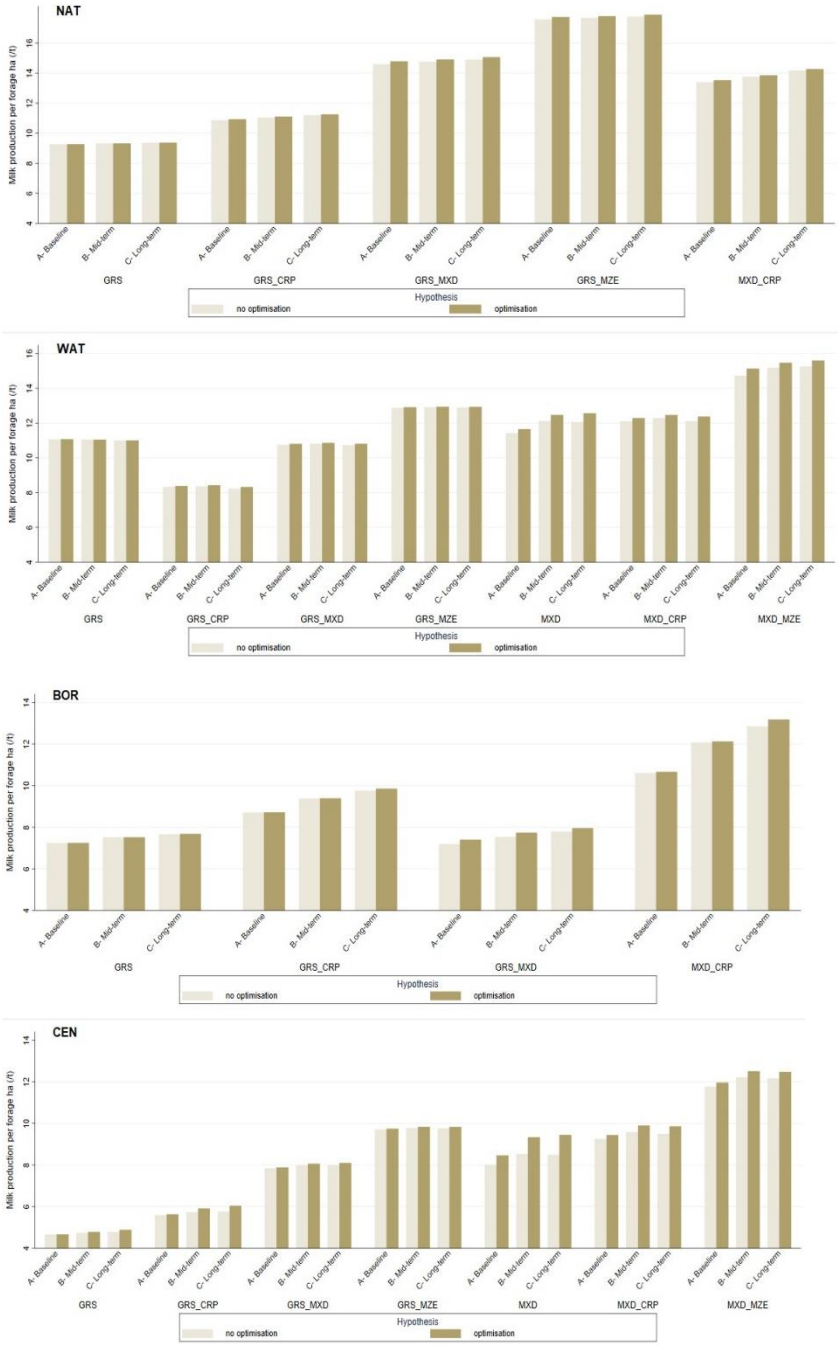

Figure 11 Predicted milk yield in each dairy farm type within the NAT, WAT, BOR and CEN climatic class, with and without farm adaptation

The Mixed system in the CEN climatic class profits the most from the optimisation scenario when comparing the baseline to either the mid-term or long-term periods.

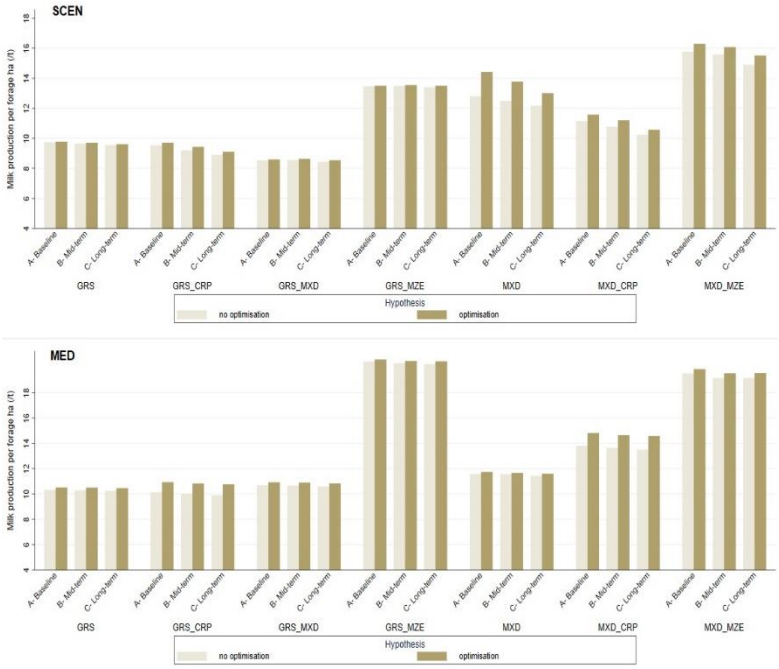

Figure 12 Predicted milk yield in each dairy farm type within the SCEN and MED climatic class, with and without farm adaptation

6.2.5. Conclusions

This analysis has demonstrated that whilst some European dairy regions are expected to suffer reduced forage productivity and therefore milk productivity, assuming the systems remain stable, other regions can expect to see improved productivity. Northern and upland areas can indeed expect higher forage yields due to longer growing seasons, providing the option of increased stocking rates, or maybe more environmentally orientated, a reduction in requirements for external feedstuffs, especially concentrates.

The analysis shows that grassland farm types are least impacted, as grassland yields are relatively stable. However, it can already be seen in the baseline, that when farmers utilise the highest yielding forage crops for their region that their productivity can remain above their current levels in virtually all regions and farm types (though of course there may be local difficulties in achieving this).

Overall, the analysis indicates that despite some potential yield challenges in the future, for the majority of producers in the impact is limited and may even be positive. However, other factors such as the potential of more erratic weather and damaging heatwaves could negate any general positive effect of a warming climate.

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6.2.7. Appendix Tables

Table 6 Predicted milk yield, stocking density, and margin (€/ha) in each dairy farm type within the NAT, WAT and BOR climatic class

Climatic class	Period		Baseline			Mid-term			Long-term			n
	Farm type	Value	Milk yield /ha (kg)	GLU /ha	Margin /ha (€)	Milk yield /ha (kg)	GLU /ha	Margin /ha (€)	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	
NAT	GRS	mean	9,255	2.07	1,114	9,310	2.09	1,126	9,354	2.10	1,132	6,237
		p50	8,515	1.98	1,062	8,569	1.99	1,074	8,609	2.00	1,082	
	GRS_CRP	mean	10,863	2.31	1,235	11,046	2.35	1,288	11,203	2.38	1,333	350
		p50	10,037	2.19	1,198	10,172	2.23	1,238	10,336	2.25	1,294	
	GRS_MXD	mean	14,590	2.49	1,583	14,744	2.52	1,626	14,890	2.54	1,675	212
		p50	14,114	2.41	1,522	14,276	2.43	1,580	14,457	2.46	1,623	
	GRS_MZE	mean	17,564	2.80	1,424	17,666	2.81	1,453	17,756	2.83	1,502	36
		p50	16,645	2.63	1,423	16,775	2.64	1,470	16,818	2.65	1,510	
	MXD_CRP	mean	13,392	2.68	1,753	13,757	2.75	1,868	14,180	2.84	2,003	48
		p50	12,742	2.55	1,620	13,122	2.60	1,704	13,549	2.67	1,829	
WAT	GRS	mean	11,060	2.17	1,773	11,039	2.16	1,756	10,996	2.15	1,738	8,575
		p50	9,586	1.95	1,538	9,589	1.95	1,519	9,569	1.94	1,504	
	GRS_CRP	mean	8,319	1.78	1,372	8,351	1.78	1,377	8,217	1.75	1,332	3,802
		p50	7,679	1.66	1,326	7,693	1.66	1,308	7,528	1.62	1,259	
	GRS_MXD	mean	10,739	2.06	1,763	10,798	2.07	1,772	10,725	2.05	1,747	4,179
		p50	9,198	1.91	1,572	9,285	1.92	1,570	9,173	1.90	1,539	
	GRS_MZE	mean	12,863	2.40	2,000	12,909	2.40	1,989	12,890	2.40	1,974	4,377
		p50	12,048	2.23	1,895	12,114	2.24	1,886	12,096	2.24	1,874	
	MXD	mean	11,422	2.10	1,708	12,118	2.23	1,922	12,061	2.22	1,895	1,433
		p50	10,647	2.00	1,606	11,317	2.15	1,834	11,180	2.11	1,797	
	MXD_CRP	mean	12,096	2.28	1,787	12,280	2.31	1,823	12,117	2.28	1,762	8,837
		p50	11,037	2.13	1,723	11,000	2.14	1,711	10,703	2.08	1,636	
	MXD_MZE	mean	14,728	2.61	1,853	15,183	2.68	1,953	15,252	2.69	1,952	5,540
		p50	13,714	2.38	1,841	14,406	2.49	1,935	14,518	2.50	1,919	
BOR	GRS	mean	7,240	1.15	868	7,510	1.20	948	7,661	1.22	989	1,144
		p50	6,603	1.07	782	6,829	1.11	848	6,950	1.13	891	
	GRS_CRP	mean	8,700	1.38	1,265	9,379	1.49	1,500	9,752	1.55	1,623	1,877
		p50	8,196	1.29	1,192	8,815	1.39	1,420	9,157	1.45	1,536	
	GRS_MXD	mean	7,190	1.18	786	7,541	1.25	894	7,786	1.29	965	112
		p50	6,852	1.12	757	7,162	1.20	858	7,385	1.24	940	
	MXD_CRP	mean	10,599	1.67	1,554	12,071	1.90	2,127	12,843	2.03	2,416	699
		p50	9,683	1.51	1,395	10,989	1.72	1,907	11,763	1.84	2,170	

Table 7 Predicted milk yield, stocking density, and margin (€/ha) in each dairy farm type within the CEN, SCEN and MED climatic class

Climatic class	Period		Baseline			Mid-term			Long-term			n
	Farm type	Value	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	
CEN	GRS	mean	4,653	1.06	646	4,731	1.08	663	4,770	1.09	670	8,321
		p50	3,873	0.97	541	3,944	0.98	559	3,975	0.99	569	
	GRS_CRP	mean	5,589	1.32	777	5,741	1.35	815	5,754	1.36	811	12,376
		p50	4,917	1.25	705	5,046	1.28	738	5,039	1.28	745	
	GRS_MXD	mean	7,840	1.71	1,379	7,979	1.74	1,415	7,986	1.74	1,415	3,063
		p50	7,380	1.65	1,337	7,523	1.68	1,370	7,532	1.67	1,363	
	GRS_MZE	mean	9,702	1.99	1,677	9,771	2.01	1,691	9,766	2.01	1,687	626
		p50	9,192	1.92	1,645	9,249	1.93	1,652	9,225	1.92	1,648	
	MXD	mean	8,007	1.88	1,345	8,518	2.00	1,492	8,480	1.99	1,482	3,110
		p50	7,375	1.80	1,211	7,885	1.93	1,346	7,782	1.91	1,299	
	MXD_CRP	mean	9,252	2.10	1,294	9,578	2.17	1,378	9,492	2.15	1,347	27,301
		p50	8,654	1.99	1,206	8,990	2.06	1,291	8,890	2.04	1,264	
	MXD_MZE	mean	11,760	2.37	1,931	12,209	2.47	2,059	12,165	2.46	2,047	2,534
		p50	11,321	2.28	1,875	11,770	2.36	1,995	11,650	2.34	1,973	
SCEN	GRS	mean	9,722	2.09	1,558	9,637	2.07	1,564	9,553	2.05	1,548	2,128
		p50	7,267	1.80	1,074	7,206	1.80	1,066	7,118	1.78	1,056	
	GRS_CRP	mean	9,529	2.11	1,494	9,186	2.03	1,406	8,897	1.96	1,322	1,071
		p50	7,436	1.72	1,124	7,163	1.63	1,020	6,905	1.59	926	
	GRS_MXD	mean	8,528	1.89	955	8,543	1.90	984	8,430	1.87	955	632
		p50	7,340	1.74	834	7,405	1.76	843	7,344	1.73	811	
	GRS_MZE	mean	13,461	2.72	1,675	13,484	2.73	1,720	13,407	2.71	1,715	522
		p50	11,598	2.44	1,588	11,594	2.46	1,606	11,581	2.45	1,615	
	MXD	mean	12,807	2.64	2,312	12,481	2.57	2,198	12,179	2.51	2,096	488
		p50	11,037	2.41	1,932	10,780	2.40	1,891	10,648	2.32	1,793	
	MXD_CRP	mean	11,136	2.39	1,213	10,763	2.31	1,117	10,242	2.19	955	1,789
		p50	9,130	2.03	830	8,822	1.94	725	8,293	1.82	568	
	MXD_MZE	mean	15,767	3.11	1,942	15,581	3.08	1,911	14,898	2.94	1,712	788
		p50	14,317	2.93	1,756	14,358	2.93	1,759	13,771	2.80	1,542	
MED	GRS	mean	10,306	2.38	1,968	10,279	2.38	1,964	10,234	2.37	1,945	836
		p50	9,080	2.11	1,719	9,022	2.10	1,719	8,969	2.08	1,699	
	GRS_CRP	mean	10,130	2.46	2,028	10,005	2.43	1,991	9,894	2.40	1,949	442
		p50	8,269	2.04	1,686	8,060	2.01	1,638	7,874	2.00	1,602	
	GRS_MXD	mean	10,685	2.11	1,201	10,660	2.10	1,194	10,578	2.07	1,153	169
		p50	5,739	1.47	8,56	5,686	1.43	855	5,603	1.42	820	
	GRS_MZE	mean	20,452	3.69	4,650	20,326	3.67	4,678	20,245	3.65	4,696	21
		p50	20,305	3.68	3,367	20,175	3.66	3,418	20,087	3.64	3,417	

MXD	mean	11,560	2.34	1,589	11,554	2.34	1,590	11,425	2.31	1,545	834
	p50	9,941	2.10	1,399	9,880	2.08	1,397	9,793	2.06	1,382	
MXD_CRP	mean	13,793	3.24	2,593	13,644	3.21	2,547	13,485	3.17	2,490	307
	p50	12,212	2.88	2,253	12,086	2.87	2,172	11,855	2.82	2,112	
MXD_MZE	mean	19,511	3.61	1,390	19,155	3.53	1,296	19,158	3.53	1,272	308
	p50	19,246	3.64	983	18,949	3.56	936	19,100	3.55	907	

Table 8 Predicted milk yield (kg/ha) by quartile of external feed dependency in each dairy farm type

Period		Baseline				Mid-term				Long-term				n
Farm type	**Value / Quartile**	**Low**	**Medium-low**	**Medium-high**	**High**	**Low**	**Medium-low**	**Medium-high**	**High**	**Low**	**Medium-low**	**Medium-high**	**High**	
GRS	mean	4,710	7,264	9,179	12,453	4,767	7,320	9,216	12,437	4,799	7,340	9,220	12,410	6,810
	p50	3,991	7,063	8,631	11,011	4,063	7,115	8,680	11,012	4,100	7,137	8,665	10,991	
GRS_CRP	mean	4,419	5,924	7,330	9,560	4,548	6,093	7,495	9,685	4,600	6,096	7,477	9,659	4,979
	p50	4,069	5,432	6,816	8,487	4,204	5,566	6,952	8,653	4,320	5,540	6,885	8,618	
GRS_MXD	mean	6,772	8,453	9,786	13,229	6,875	8,538	9,876	13,310	6,831	8,503	9,844	13,273	2,091
	p50	6,620	7,937	8,982	11,864	6,709	7,979	9,073	11,974	6,588	7,941	9,054	11,972	
GRS_MZE	mean	9,998	11,607	12,846	16,044	10,051	11,645	12,894	16,089	10,042	11,627	12,868	16,054	1,395
	p50	9,235	10,656	12,088	14,684	9,270	10,664	12,145	14,758	9,200	10,639	12,099	14,735	
MXD	mean	6,805	8,704	10,389	13,128	7,202	9,166	10,870	13,448	7,068	9,070	10,825	13,424	1,471
	p50	6,288	8,190	9,648	11,877	6,667	8,573	10,118	12,468	6,508	8,449	10,096	12,508	
MXD_CRP	mean	7,510	9,245	10,816	12,622	7,768	9,594	11,145	12,801	7,690	9,520	11,051	12,616	9,745
	p50	7,119	8,675	9,985	11,638	7,393	9,014	10,258	11,778	7,357	8,934	10,110	11,599	
MXD_MZE	mean	11,544	13,782	14,721	16,605	11,989	14,178	15,012	16,956	12,022	14,217	14,941	16,840	2,295
	p50	10,879	12,719	13,189	15,207	11,314	13,133	13,561	15,670	11,281	13,043	13,494	15,677	
UPL	mean	5,087	6,163	7,053	8,201	5,285	6,321	7,182	8,270	5,425	6,448	7,284	8,348	3,826
	p50	4,718	5,433	5,830	6,305	4,925	5,589	5,986	6,458	5,104	5,725	6,112	6,591	

Table 9 Predicted milk yield by quartile of external feed dependency in each climatic class

Period		Baseline				Mid-term				Long-term				n
Climatic class	**Value / Quartile**	**Low**	**Medium -low**	**Medium -high**	**High**	**Low**	**Medium -low**	**Medium -high**	**High**	**Low**	**Medium -low**	**Medium -high**	**High**	
NAT	mean	7,799	8,676	9,907	11,991	7,574	8,739	9,984	12,061	7,879	8,794	10,042	12,111	1,725
	p50	7,511	8,293	9,359	11,156	7,066	8,349	9,414	11,197	7,260	8,399	9,467	11,243	
WAT	mean	9,507	11,037	12,096	14,446	8,590	11,206	12,209	14,511	9,155	11,150	12,122	14,449	9,185
	p50	8,543	10,047	11,340	13,280	7,904	10,046	11,416	13,383	8,382	9,881	11,310	13,341	
BOR	mean	7,491	8,696	9,091	9,018	5,992	9,526	9,643	9,308	5,987	9,970	9,960	9,491	960
	p50	6,882	8,101	8,434	8,282	5,838	8,865	9,033	8,612	5,744	9,235	9,364	8,796	
CEN	mean	5,766	7,150	8,558	9,593	4,848	7,430	8,843	9,823	5,065	7,403	8,791	9,762	14,332
	p50	5,624	7,042	8,353	9,247	4,563	7,326	8,641	9,445	4,762	7,239	8,538	9,330	
SCEN	mean	7,332	9,268	11,932	15,636	7,976	9,103	11,660	15,436	7,868	8,801	11,294	15,208	1,854
	p50	6,419	8,125	10,131	14,113	7,227	7,936	9,898	13,984	7,148	7,717	9,651	13,806	
MED	mean	8,102	11,584	15,213	13,394	7,334	11,503	15,144	13,335	7,144	11,416	15,052	13,267	729
	p50	7,353	9,696	13,678	11,793	6,686	9,642	13,639	11,702	6,535	9,523	13,524	11,646	
AUPL	mean	7,259	10,097	7,649	8,216	7,863	10,276	7,812	8,394	7,931	10,563	7,870	8,437	16
	p50	6,882	10,892	6,990	8,001	7,559	10,994	7,159	8,165	7,621	11,341	7,183	8,221	
CUPL	mean	4,570	5,569	6,056	6,061	7,160	5,790	6,256	6,236	6,860	5,972	6,420	6,394	301
	p50	4,307	5,013	5,189	5,144	6,307	5,205	5,344	5,312	6,118	5,328	5,483	5,472	
MUPL	mean	7,494	9,635	12,015	13,412	9,760	9,459	11,837	13,247	9,705	9,293	11,689	13,157	791
	p50	6,862	8,537	10,727	11,550	8,620	8,330	10,554	11,397	8,398	8,147	10,458	11,350	

Table 10 Predicted milk yield by quartile of external feed dependency in each dairy farm type within the NAT and WAT climatic class

Climatic class	Period		Baseline				Mid-term				Long-term				n
	Farm type	Value / Quartile	Low	Medium-low	Medium-high	High	Low	Medium-low	Medium-high	High	Low	Medium-low	Medium-high	High	
NAT	GRS	mean	7,470	8,405	9,517	11,630	7,517	8,458	9,578	11,687	7,565	8,500	9,623	11,728	1,559
		p50	7,308	8,143	9,035	10,932	7,354	8,185	9,112	10,986	7,414	8,228	9,184	11,029	
	GRS_CRP	mean	8,828	9,812	10,700	14,136	8,956	9,976	10,875	14,405	9,083	10,129	11,048	14,576	87
		p50	8,528	9,513	10,298	13,463	8,557	9,618	10,458	13,803	8,791	9,822	10,606	13,970	
	GRS_MXD	mean	1,104	13,150	15,040	19,130	11,165	13,289	15,201	19,321	11,303	13,438	15,355	19,464	53
		p50	1,075	12,365	14,667	18,126	10,777	12,521	14,884	18,236	10,984	12,651	15,025	18,263	
WAT	GRS	mean	7,634	9,901	11,674	15,031	7,633	9,906	11,671	14,947	7,597	9,878	11,641	14,871	2,143
		p50	6,892	9,181	10,799	13,149	6,898	9,192	10,828	13,083	6,847	9,151	10,782	13,035	
	GRS_CRP	mean	7,110	7,776	8,458	9,933	7,178	7,804	8,472	9,953	7,019	7,670	8,344	9,837	950
		p50	6,748	7,282	7,913	9,015	6,826	7,260	7,919	9,078	6,600	7,035	7,739	8,930	
	GRS_MXD	mean	7,737	9,128	10,715	15,382	7,791	9,180	10,777	15,450	7,691	9,111	10,711	15,393	1,044
		p50	7,373	8,555	9,949	14,237	7,390	8,515	10,008	14,292	7,223	8,407	9,947	14,248	
	GRS_MZE	mean	1,033	11,684	12,999	16,442	10,378	11,722	13,050	16,487	10,379	11,705	13,025	16,455	1,094
		p50	9,357	10,827	12,340	15,264	9,339	10,866	12,422	15,317	9,310	10,828	12,415	15,280	
	MXD	mean	9,254	10,793	11,660	13,989	9,866	11,641	12,431	14,542	9,516	11,617	12,467	14,653	358
		p50	8,810	10,333	11,038	12,731	9,331	11,102	11,753	13,433	8,927	10,678	11,670	13,647	
	MXD_CRP	mean	1,052	11,680	12,104	14,076	10,859	11,927	12,173	14,161	10,765	11,817	11,959	13,928	2,209
		p50	9,408	10,414	11,257	13,142	9,447	10,323	11,181	13,152	9,154	10,080	10,913	12,877	
	MXD_MZE	mean	1,282	14,170	14,908	17,014	13,439	14,614	15,242	17,437	13,696	14,729	15,216	17,366	1,385
		p50	1,245	13,029	13,624	15,817	13,375	13,538	13,994	16,435	13,676	13,514	13,889	16,401	

Table 11 Predicted milk yield by quartile of external feed dependency in each dairy farm type within the BOR and CEN climatic class

Climatic class	Period		Baseline				Mid-term				Long-term				n
	Farm type	Value / Quartile	Low	Medium-low	Medium-high	High	Low	Medium-low	Medium-high	High	Low	Medium-low	Medium-high	High	
BOR	GRS	mean	6,227	6,941	7,594	8,197	6,732	7,208	7,761	8,340	6,988	7,359	7,866	8,432	286
		p50	5,604	6,331	6,783	7,610	6,081	6,520	6,937	7,732	6,325	6,643	7,035	7,808	
	GRS_CRP	mean	6,965	8,459	9,213	10,168	7,865	9,198	9,809	10,649	8,332	9,600	10,143	10,937	469
		p50	6,484	7,813	8,692	9,330	7,249	8,490	9,311	9,899	7,634	8,851	9,632	10,192	
	GRS_MXD	mean	4,731	7,983	8,489	7,558	5,198	8,390	8,768	7,809	5,470	8,661	8,998	8,015	28
		p50	4,159	7,300	8,468	7,503	4,652	7,670	8,806	7,775	4,945	7,917	9,049	8,008	
	MXD_CRP	mean	8,516	10,198	10,883	12,813	10,304	11,813	12,236	13,940	11,195	12,652	12,959	14,575	175
		p50	7,840	9,359	9,794	11,680	9,636	10,787	11,140	12,903	10,411	11,573	11,828	13,515	
CEN	GRS	mean	2,870	3,821	5,365	6,557	2,953	3,901	5,447	6,622	3,021	3,948	5,474	6,636	2,080
		p50	2,677	3,389	4,778	5,810	2,762	3,463	4,824	5,877	2,833	3,528	4,829	5,861	
	GRS_CRP	mean	4,057	4,719	5,974	7,604	4,198	4,873	6,135	7,756	4,275	4,920	6,120	7,701	3,094
		p50	3,911	4,437	5,569	6,960	4,041	4,571	5,700	7,061	4,159	4,621	5,640	6,962	
	GRS_MXD	mean	5,973	7,423	8,303	9,663	6,119	7,563	8,441	9,796	6,143	7,567	8,438	9,799	766
		p50	5,689	7,200	7,922	9,136	5,841	7,360	8,081	9,256	5,822	7,402	8,059	9,254	
	GRS_MZE	mean	7,883	9,252	10,054	11,629	7,971	9,323	10,116	11,685	7,982	9,322	10,109	11,660	156
		p50	7,526	9,000	9,746	10,879	7,612	9,111	9,759	10,931	7,577	9,110	9,731	10,908	
	MXD	mean	6,032	7,265	8,696	10,036	6,517	7,753	9,231	10,572	6,441	7,704	9,219	10,557	777
		p50	5,733	6,843	8,529	9,605	6,195	7,282	8,930	10,130	6,125	7,266	9,026	10,103	
	MXD_CRP	mean	7,251	8,494	9,841	11,422	7,524	8,839	10,211	11,740	7,463	8,775	10,130	11,601	6,825
		p50	6,902	8,078	9,384	10,815	7,182	8,423	9,763	11,142	7,170	8,358	9,683	10,998	
	MXD_MZE	mean	9,746	11,360	12,234	13,703	10,274	11,802	12,652	14,110	10,300	11,776	12,590	13,995	633
		p50	9,368	11,030	11,876	13,017	9,900	11,449	12,287	13,474	9,928	11,363	12,174	13,399	

Table 12 Predicted milk yield by quartile of external feed dependency in each dairy farm type within the SCEN and MED climatic class

Climatic class	Period		Baseline				Mid-term				Long-term				n
	Farm type / Quartile		Low	Medium-low	Medium-high	High	Low	Medium-low	Medium-high	High	Low	Medium-low	Medium-high	High	
SCEN	GRS	mean	5,697	7,290	10,707	15,194	5,666	7,217	10,566	15,100	5,588	7,131	10,464	15,028	532
		p50	5,348	6,639	9,772	14,465	5,388	6,610	9,632	14,344	5,317	6,559	9,509	14,238	
	GRS_CRP	mean	6,096	7,209	9,572	15,258	5,867	6,930	9,195	14,772	5,597	6,664	8,885	14,463	268
		p50	5,801	6,509	7,538	13,743	5,663	6,075	7,250	13,260	5,314	5,946	6,974	12,938	
	GRS_MXD	mean	6,435	8,004	8,332	11,342	6,540	8,057	8,279	11,297	6,459	7,942	8,143	11,176	158
		p50	6,621	7,907	7,165	8,228	6,746	8,092	7,048	8,388	6,684	8,063	6,844	8,424	
	GRS_MZE	mean	9,656	12,022	15,393	16,788	9,697	12,067	15,370	16,815	9,624	12,006	15,268	16,744	130
		p50	9,400	11,923	15,512	12,956	9,393	11,929	15,458	13,086	9,357	11,920	15,280	12,999	
	MXD	mean	7,392	11,245	13,384	19,209	7,130	11,017	13,046	18,730	6,856	10,700	12,717	18,441	122
		p50	6,941	10,848	12,277	19,374	6,946	10,738	11,883	18,701	6,630	10,648	11,732	18,480	
	MXD_CRP	mean	7,311	10,480	11,853	14,908	6,934	10,196	11,483	14,447	6,475	9,686	10,933	13,882	447
		p50	6,184	9,632	9,369	11,859	5,807	9,426	9,109	11,363	5,327	8,903	8,557	10,812	
	MXD_MZE	mean	11,069	13,820	17,733	20,448	11,037	13,662	17,361	20,264	10,444	13,015	16,540	19,593	197
		p50	10,809	13,790	17,659	18,873	10,838	13,781	17,447	18,714	10,462	13,202	16,472	18,041	
MED	GRS	mean	7,455	10,114	12,654	11,002	7,430	10,100	12,635	10,953	7,381	10,058	12,595	10,901	209
		p50	6,560	9,410	11,727	9,943	6,519	9,398	11,689	9,893	6,524	9,382	11,581	9,838	
	GRS_CRP	mean	6,903	8,044	11,078	14,516	6,752	7,907	10,979	14,405	6,648	7,792	10,865	14,292	110
		p50	6,778	7,835	9,640	13,471	6,585	7,659	9,715	13,335	6,525	7,480	9,694	13,225	
	GRS_MXD	mean	4,211	13,334	14,371	10,980	4,157	13,365	14,355	10,917	4,054	13,294	14,270	10,847	42
		p50	3,094	5,169	6,810	8,132	2,998	5,243	6,833	8,036	2,849	5,228	6,754	7,933	
	MXD	mean	7,820	10,589	13,201	14,638	7,796	10,597	13,201	14,633	7,675	10,457	13,055	14,523	208
		p50	6,492	9,281	11,275	14,065	6,617	9,309	11,285	14,006	6,422	9,251	10,999	13,890	

MXD_CRP	mean	10,011	11,460	16,155	17,595	9,779	11,210	16,073	17,567	9,623	11,062	15,922	17,383	77
	p50	9,350	10,804	15,689	15,756	9,180	10,866	15,514	15,511	9,159	10,664	15,652	15,347	
MXD_MZE	mean	11,441	20,606	22,584	23,415	11,006	20,278	22,260	23,077	10,930	20,302	22,268	23,131	77
	p50	10,107	20,699	22,447	23,340	9,630	20,490	22,082	23,013	9,752	20,472	21,897	22,691	

Table 13 Predicted non-permanent forage areas and predicted milk yield, stocking density, and margin (€/ha) in each dairy farm type in the optimisation scenario

Period		Baseline						Mid-term						Long-term						n
Farm type	Value	Maize area (%)	TG area (%)	Other fodder area (%)	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	Maize area (%)	TG area (%)	Other fodder area (%)	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	Maize area (%)	TG area (%)	Other fodder area (%)	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	
GRS	mea	5	21	2	8,417	1.77	1,308	13	13	2	8,466	1.78	1,317	13	11	5	8,490	1.79	1,319	27,241
	p50	0	0	0	7,488	1.66	1,137	0	0	0	7,530	1.67	1,144	0	0	0	7,545	1.67	1,143	
GRS_CRP	mea	13	31	2	6,874	1.51	1,107	29	15	2	7,105	1.56	1,168	29	11	6	7,190	1.58	1,189	19,918
	p50	0	0	0	6,077	1.38	990	16	0	0	6,239	1.43	1,052	15	0	0	6,296	1.44	1,064	
GRS_MXD	mea	18	18	4	9,622	1.93	1,616	31	8	1	9,725	1.95	1,639	24	10	6	9,711	1.95	1,631	8,367
	p50	0	0	0	8,413	1.80	1,478	26	0	0	8,516	1.82	1,494	22	0	0	8,459	1.82	1,484	
GRS_MZE	mea	28	23	5	12,66	2.40	2,009	43	11	1	12,70	2.40	1,997	36	10	8	12,69	2.40	1,985	5,582
	p50	27	0	0	11,70	2.23	1,883	36	0	0	11,75	2.24	1,877	34	0	0	11,75	2.24	1,869	
MXD	mea	44	20	13	10,21	2.17	1,769	60	4	14	10,81	2.31	1,928	55	8	14	10,82	2.31	1,922	5,884
	p50	45	0	0	9,081	2.00	1,529	62	0	0	9,666	2.18	1,721	60	0	0	9,672	2.19	1,714	
MXD_CRP	mea	36	15	2	10,24	2.20	1,594	49	4	1	10,61	2.28	1,686	45	4	5	10,55	2.26	1,662	38,981
	p50	33	0	0	9,415	2.06	1,509	44	0	0	9,764	2.14	1,608	41	0	0	9,712	2.12	1,580	
MXD_MZE	mea	40	31	6	14,51	2.69	2,066	60	9	9	14,84	2.75	2,124	55	10	12	14,86	2.75	2,116	9,180
	p50	45	0	0	13,28	2.46	1,978	65	0	0	13,77	2.55	2,049	60	0	0	13,83	2.57	2,036	
UPL	mea	16	9	8	6,727	1.56	1,230	17	8	8	6,918	1.62	1,295	18	2	15	7,010	1.64	1,319	15,304
	p50	0	0	0	5,568	1.32	992	0	0	0	5,760	1.36	1,056	0	0	0	5,897	1.39	1,098	

Pe	Baseline					Mid-term					Long-term					n
Cima	Maize area (%)	TG area (%)	Other fodder area (%)	Milk yield /ha (kg)	GLU /ha	Margin/ha	Maize area (%)	TG area (%)	Other fodder area (%)	Milk yield /ha (kg)	GLU /ha	Margin/ha	Maize area (%)	TG area (%)	Other fodder area (%)	Milk yield /ha (kg)	GLU /ha	Margin/ha	

Table 14 Predicted non-permanent forage areas and predicted milk yield, stocking density, and margin (€/ha) in each climatic class in the optimisation scenario

Period		Baseline						Mid-term						Long-term						
Climatic class	Value	Maize area (%)	TG area (%)	Other fodder area (%)	Milk yield /ha (kg)	GLU/ ha	Margin/ ha (€)	Maize area (%)	TG area (%)	Other fodder area (%)	Milk yield /ha (kg)	GLU/ ha	Margin/ ha (€)	Maize area (%)	TG area (%)	Other fodder area (%)	Milk yield /ha (kg)	GLU/ ha	Margin /ha (€)	n
NAT	mean	0	18	0	9,613	2.11	1,143	0	18	0	9,678	2.13	1,158	0	18	0	9,736	2.14	1,170	6,902
	p50	0	10	0	8,749	2.01	1,084	0	10	0	8,801	2.03	1,097	0	10	0	8,852	2.04	1,107	
WAT	mean	23	21	4	11,905	2.26	1,782	41	4	2	1,204	2.28	1,797	35	3	9	1,201	2.27	1,777	36,743
	p50	0	0	0	10,720	2.08	1,653	34	0	0	1,081	2.11	1,661	28	0	0	1,071	2.09	1,628	
BOR	mean	0	97	0	8,601	1.37	1,192	0	97	0	9,291	1.48	1,438	14	83	0	9,765	1.55	1,636	3,842
	p50	0	100	0	7,987	1.26	1,083	0	100	0	8,623	1.37	1,315	0	100	0	9,082	1.44	1,490	
CEN	mean	29	16	1	7,899	1.79	1,152	43	3	0	8,278	1.88	1,248	43	3	0	8,306	1.88	1,248	57,331
	p50	18	0	0	7,514	1.70	1,062	37	0	0	7,947	1.79	1,158	37	0	0	7,940	1.78	1,150	
SCEN	mean	28	36	1	11,355	2.41	1,603	36	28	1	1,114	2.36	1,559	9	33	24	1,079	2.28	1,449	7,418
	p50	0	13	0	9,350	2.10	1,140	0	0	0	9,240	2.07	1,122	0	0	0	8,895	2.01	1,039	
MED	mean	22	0	58	12,457	2.69	1,998	10	0	70	1,236	2.67	1,971	14	0	66	1,231	2.66	1,951	2,917
	p50	0	0	98	10,508	2.38	1,741	0	0	100	1,040	2.36	1,723	0	0	100	1,034	2.34	1,714	
AUPL	mean	6	5	0	8,352	1.55	1,364	0	11	0	8,573	1.60	1,424	6	5	0	8,696	1.62	1,451	67
	p50	0	0	0	7,969	1.49	1,237	0	0	0	8,136	1.52	1,313	0	0	0	8,119	1.55	1,333	
CUPL	mean	15	11	0	5,652	1.40	1,031	16	11	0	5,919	1.47	1,118	22	2	3	6,068	1.50	1,158	12,070
	p50	0	0	0	4,927	1.21	867	0	0	0	5,147	1.26	937	0	0	0	5,306	1.29	984	
MUPL	mean	19	3	40	10,789	2.19	1,768	21	0	41	1,068	2.17	1,750	2	0	60	1,056	2.15	1,711	3,167
	p50	0	0	26	9,071	1.95	1,533	0	0	27	9,002	1.93	1,527	0	0	70	8,874	1.91	1,502	

Table 15 Predicted milk yield, stocking density, and margin (€/ha) in each dairy farm type within the NAT, WAT and BOR climatic class in the optimisation scenario

Climatic class	Period		Baseline			Mid-term			Long-term			n
	Farm type	Value	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	
NAT	GRS	mean	9,261	2.08	1,114	9,315	2.09	1,126	9,359	2.10	1,132	6,237
		p50	8,526	1.98	1,062	8,576	1.99	1,073	8,612	2.00	1,082	
	GRS_CRP	mean	10,933	2.32	1,249	11,104	2.36	1,298	11,259	2.39	1,342	350
		p50	10,059	2.21	1,225	10,224	2.24	1,262	10,387	2.27	1,303	
	GRS_MXD	mean	14,781	2.53	1,606	14,901	2.55	1,638	15,054	2.57	1,689	212
		p50	14,279	2.44	1,572	14,401	2.45	1,594	14,614	2.48	1,665	
	GRS_MZE	mean	17,738	2.83	1,421	17,800	2.84	1,442	17,883	2.85	1,491	36
		p50	16,770	2.66	1,409	16,858	2.66	1,397	16,906	2.68	1,417	
	MXD_CRP	mean	13,527	2.71	1,784	13,857	2.77	1,887	14,260	2.86	2,015	48
		p50	12,890	2.59	1,643	13,306	2.64	1,704	13,663	2.70	1,861	
WAT	GRS	mean	11,068	2.17	1,774	11,045	2.16	1,756	11,006	2.16	1,739	8,575
		p50	9,590	1.95	1,538	9,590	1.95	1,520	9,572	1.94	1,505	
	GRS_CRP	mean	8,379	1.79	1,380	8,427	1.80	1,388	8,315	1.77	1,349	3,802
		p50	7,755	1.67	1,333	7,756	1.68	1,323	7,608	1.65	1,276	
	GRS_MXD	mean	10,797	2.07	1,765	10,857	2.08	1,770	10,804	2.07	1,749	4,179
		p50	9,245	1.92	1,569	9,329	1.93	1,572	9,219	1.92	1,542	
	GRS_MZE	mean	12,908	2.40	1,977	12,941	2.41	1,953	12,931	2.41	1,937	4,377
		p50	12,089	2.24	1,863	12,139	2.25	1,849	12,127	2.25	1,838	
	MXD	mean	11,653	2.14	1,738	12,467	2.30	1,970	12,570	2.32	1,993	1,433
		p50	10,854	2.05	1,654	11,646	2.21	1,871	11,589	2.20	1,901	
	MXD_CRP	mean	12,282	2.32	1,799	12,461	2.35	1,822	12,368	2.32	1,780	8,837
		p50	11,160	2.16	1,723	11,169	2.17	1,717	10,950	2.13	1,653	
	MXD_MZE	mean	15,127	2.68	1,916	15,471	2.74	1,952	15,595	2.76	1,965	5,540
		p50	14,108	2.44	1,873	14,665	2.53	1,923	14,863	2.57	1,934	
BOR	GRS	mean	7,243	1.15	868	7,514	1.20	947	7,675	1.22	1,004	1,144
		p50	6,605	1.07	782	6,841	1.11	848	6,961	1.13	900	
	GRS_CRP	mean	8,712	1.39	1,267	9,391	1.50	1,501	9,852	1.57	1,692	1,877
		p50	8,202	1.29	1,194	8,822	1.39	1,420	9,259	1.46	1,601	
	GRS_MXD	mean	7,398	1.22	812	7,739	1.28	914	7,954	1.32	990	112
		p50	7,038	1.16	791	7,388	1.23	906	7,522	1.27	974	
	MXD_CRP	mean	10,659	1.68	1,572	12,122	1.91	2,141	13,179	2.08	2,610	699
		p50	9,770	1.53	1,408	11,026	1.73	1,918	12,155	1.90	2,435	

Table 16 Predicted milk yield, stocking density, and margin (€/ha) in each dairy farm type within the CEN, SCEN and MED climatic class in the optimisation scenario

Climatic class	Period		Baseline			Mid-term			Long-term			n
	Farm type	Value	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	Milk yield /ha (kg)	GLU /ha	Margin/ha (€)	
CEN	GRS	mean	4,659	1.06	647	4,782	1.09	673	4,876	1.11	690	8,321
		p50	3,880	0.97	543	3,999	1.00	576	4,077	1.02	603	
	GRS_CRP	mean	5,628	1.33	786	5,906	1.40	852	6,033	1.42	877	12,376
		p50	4,969	1.26	716	5,269	1.32	793	5,454	1.34	825	
	GRS_MXD	mean	7,884	1.72	1,386	8,056	1.76	1,429	8,094	1.77	1,436	3,063
		p50	7,406	1.66	1,340	7,572	1.69	1,385	7,629	1.70	1,386	
	GRS_MZE	mean	9,740	2.00	1,665	9,833	2.02	1,683	9,828	2.02	1,679	626
		p50	9,241	1.92	1,635	9,349	1.94	1,652	9,300	1.94	1,637	
	MXD	mean	8,463	2.00	1,451	9,338	2.22	1,693	9,443	2.25	1,724	3,110
		p50	7,865	1.92	1,347	8,721	2.14	1,585	8,783	2.18	1,587	
	MXD_CRP	mean	9,435	2.14	1,327	9,895	2.25	1,443	9,854	2.24	1,423	27,301
		p50	8,883	2.03	1,249	9,363	2.13	1,379	9,345	2.12	1,358	
	MXD_MZE	mean	11,959	2.41	1,942	12,507	2.53	2,096	12,474	2.52	2,088	2,534
		p50	11,570	2.32	1,893	12,117	2.43	2,045	11,987	2.43	2,019	
SCEN	GRS	mean	9,769	2.10	1,579	9,701	2.09	1,593	9,607	2.06	1,571	2,128
		p50	7,341	1.80	1,076	7,246	1.81	1,072	7,161	1.79	1,069	
	GRS_CRP	mean	9,709	2.15	1,563	9,427	2.09	1,500	9,092	2.01	1,391	1,071
		p50	7,533	1.76	1,147	7,342	1.71	1,096	7,036	1.62	987	
	GRS_MXD	mean	8,587	1.91	957	8,631	1.92	996	8,536	1.90	971	632
		p50	7,371	1.74	823	7,463	1.78	846	7,459	1.75	833	
	GRS_MZE	mean	13,493	2.73	1,627	13,537	2.74	1,680	13,493	2.73	1,684	522
		p50	11,647	2.44	1,539	11,639	2.47	1,569	11,668	2.47	1,587	
	MXD	mean	14,417	2.99	2,968	13,769	2.85	2,709	12,999	2.69	2,400	488
		p50	12,655	2.82	2,809	12,425	2.72	2,515	11,732	2.57	2,125	
	MXD_CRP	mean	11,572	2.48	1,315	11,192	2.40	1,216	10,569	2.26	1,014	1,789
		p50	9,596	2.15	871	9,280	2.03	820	8,604	1.90	634	
	MXD_MZE	mean	16,292	3.22	2,035	16,066	3.18	1,985	15,510	3.07	1,829	788
		p50	14,727	3.03	1,789	14,823	3.02	1,792	14,397	2.92	1,649	
MED	GRS	mean	10,508	2.44	2,057	10,491	2.43	2,057	10,461	2.43	2,043	836
		p50	9,263	2.16	1,804	9,280	2.15	1,798	9,258	2.14	1,789	
	GRS_CRP	mean	10,919	2.66	2,386	10,812	2.64	2,356	10,751	2.62	2,335	442
		p50	9,059	2.24	2,050	9,019	2.23	2,030	8,963	2.22	2,021	
	GRS_MXD	mean	10,914	2.16	1,219	10,890	2.15	1,213	10,831	2.13	1,180	169
		p50	6,116	1.47	846	6,062	1.46	846	6,021	1.44	837	
	GRS_MZE	mean	20,613	3.72	4,645	20,506	3.70	4,685	20,468	3.69	4,723	21
		p50	20,534	3.70	3,405	20,370	3.68	3,452	20,276	3.68	3,446	
	MXD	mean	11,733	2.38	1,653	11,659	2.36	1,623	11,587	2.34	1,595	834
		p50	10,267	2.12	1,437	10,139	2.10	1,432	9,984	2.10	1,428	
	MXD_CRP	mean	14,804	3.49	3,018	14,654	3.46	2,973	14,577	3.44	2,948	307
		p50	13,030	3.11	2,699	12,926	3.10	2,616	12,831	3.06	2,638	
	MXD_MZE	mean	19,862	3.68	1,442	19,523	3.61	1,361	19,550	3.62	1,357	308
		p50	19,529	3.67	982	19,172	3.60	895	19,309	3.65	900	

6.3. Annexe 3

Does organic certification make economic sense for dairy farmers in Europe? - A latent class counterfactual analysis

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Declaration of interest

The authors have no competing interests to declare.

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6.3.1. Abstract

Certification in agriculture ensures compliance with tangible standards and should generate economic opportunities for farmers. This study quantifies the economic impacts of organic certification in dairy farming across Europe, using farm-level FADN data from 25 countries while accounting for heterogeneity through a class splitting model. Four distinct classes with dairy farm enterprises operating under similar production technologies were identified in order to assess gross margin and efficiency differences among certified and non-certified farms. Depending on the nature of the selection bias, treatment effects were estimated either through an endogenous treatment model or through entropy balancing, With the exception of dairy farming in warm regions, the results suggest that organic certification pays off for dairy farmers in Europe, while slightly increasing their efficiency. Significant certification effects range from 37% to 70% in terms of profitability gains, and from 3% to 5% in terms of efficiency gains.

Keywords: Gross margins, efficiency, stochastic frontier, endogenous treatment model

6.3.2. Introduction

Agroecology is increasingly recognised as an important strategy for achieving more sustainable agricultural and food systems (FAO, 2018; HLPE, 2019). To work for farmers, it needs to make economic sense. This requires that agroecology interventions are systematically evaluated in terms of their economic potential. Certification plays a key role in this context. Organic farming by its nature entails the application of many agroecological principles, but is in addition formalised by using standards to certify compliance with these principles (Mockshell and Villarino, 2019). Organic agriculture is globally growing rapidly (Willer and Lernoud, 2019) and, under the right conditions, the prospects for farmers created through organic certification can make an important contribution to sustainable rural livelihoods (Crowder and Reganold, 2015).

Sustainability standards have been evaluated for a wide range of outcomes, such as gender equality (Meemken and Qaim, 2018), adoption of good agricultural practices (Ibanez and Blackman, 2016) or pesticide use reduction (Schreinemachers et al., 2012). Many impact evaluation studies related to sustainability standards seek to examine economic effects (Schleifer and Sun, 2020). One key objective of certification, including organic standards, is to generate economic opportunities for farmers. However, certification costs have been found to discourage farmers from becoming certified (Dabbert et al., 2014). Increasing case study evidence from a low- and middle-income country context (e.g.; Mendoza, 2004; Bolwig et al., 2009; Ssebunya et al., 2019; Tran and Goto, 2019;) as well as from a high-income country context (e.g. Moakes et al., 2016; Hoop et al., 2017) point towards financial benefits of organic certification. A meta-study of the competitiveness of organic farming showed higher profitability and benefit-cost ratios for organic certified farms as compared to non-certified farms (Crowder and Reganold, 2015). Additionally, a recent review paper compiled empirical evidence on the economic potential of agroecology in Europe, including data from several certified organic cases (van der Ploeg et al., 2019). As regards efficiency, less studies are available though. The literature generally suggests that organic farms are less efficient, especially when

measured against the same production frontier as conventional farms (Oude Lansink et al. 2002; Kumbhakar et al., 2009; Mayen et al., 2010).

We add to the existing literature by conducting a cross-country efficiency and productivity analysis of a large representative data set covering dairy farms across 25 EU countries. The dairy industry, both organic and conventional, is highly competitive and, in terms of output value, the second biggest agricultural activity in the EU after vegetable production (EPRS, 2018). Organic cow milk production in Europe has almost doubled between 2008 and 2017, with latest figures indicating an output of 4.7 million metric tons. The organic market share ranges from less than 1% to above 10% in some Central European countries (Willer and Lernoud, 2019). Changing consumer preferences and pressures on milk prices are considered as key drivers behind rising numbers of conversion among dairy farmers (Bouttes et al., 2019). Certification is crucial for managing compliance with agroecological farming requirements and ensuring price premiums.

To account for productivity and efficiency effects, this study analyses the economic consequences of standard implementation with two key performance indicators: Gross margins are calculated to assess impacts on dairy enterprise profitability, and efficiency scores are estimated to provide insights into the conversion of production inputs into economic output. In the framework of a counterfactual analysis, the two selected outcome measures can explain how organic certification influences farm performance, while taking into account possible trade-offs or synergies between profitability and efficiency.

The novelty of this research rests upon its scope and methodological approach. To the knowledge of the authors, no rigorous impact studies exist that evaluate the profitability and efficiency effects of organic certification at a regional scale, with other similar economic impact studies being location-specific and focusing on farm incomes only. The cross-country impact estimates are of wide relevance for practitioners and policy-makers in Europe and beyond. A key challenge in covering almost the entire EU dairy sector is to account for contextual factors. By combining a latent class model with state-of-the-art impact evaluation methods for observational data, the study quantifies the context-specific economic effects of organic certification. This allows drawing a more precise and comprehensive picture of certification impacts. The broad geographic coverage and the significance of the dairy sector should foster a better understanding of the wider economic implications of organic certification.

The analysis finds that obtaining certification generally makes economic sense for organic dairy farmers in Europe. The next section of the paper explains data sources, the class splitting approach and the econometric model used to assess certification impacts. Impact estimates for all four classes are then presented in section three and discussed in section four of the paper. The final section also includes some relevant policy implications that can be derived from the analysis.

6.3.3. Material and Methods

6.3.3.1. Data

The study utilises detailed economic data from the Farm Accountancy Data Network (FADN, 2018) database for farm types that include cattle systems for the period 2004 until 2013 (the latest year that data was available for analysis in 2019). It covers 25 EU member countries,

representing a large diversity of farming across Europe. The organic certification variable in the dataset is specified in line with the regulations that govern the EU organic standard (Reg. EC No. 834/2007 and Reg. EC No. 889/2008). This implies for instance more adequate space for cows, no preventive use of antibiotics and livestock feed of organic origin.

To identify farms with a significant dairy enterprise, only those farms with a minimum of 35% of economic output from the dairy enterprise (specialisation rate) are included in the dataset, as per FADN recommendations (FADN, 2018). The selected dataset contains more than 140,000 dairy enterprise observations, however it does not represent a complete balanced panel data structure, as there is no exact overlap among farms from one year to another. While certain farms remain in the sample, some drop out and others are added. Between 2004 and 2013 only 22 % of farms are identical (between 1% and 56% depending on the country). Each year ca. 18% of farms dropped out and were replaced. This complicates time-series analysis, as impact studies need to compare the same farms across time. Therefore, the present study relies on a pooled subset of data including observations from the three most recent years in the entire dataset, i.e. 2011, 2012 and 2013. Year-dummies are included in the analyses where needed to account for temporal effects. In line with the classification explained in the following section, summary statistics for key variables used in the analysis are provided in Table 1.

All inputs, aside from land and labour, as well as output are measured in monetary terms and have been calculated according to the proposed FADN calculation methodology (FADN, 2018). The output variable includes direct revenues from milk sales, but no subsidies. Land refers to forage area for dairy cows. Labour input includes hours from hired and own labour. Feed costs comprise coarse fodder, non-fodder and concentrate expenditures, while forage costs were estimated based on seed, fertiliser, and pesticide expenditures. The variable labelled as other direct costs sums up expenditures for herd renewal, veterinary services and contract work. Various data on farm characteristics was used in different parts of the analysis. As outlined in Table 1 this includes information on the area of the farm, economic size of the farm, stocking density, subsidy payments, farm assets, available forage area, degree of specialisation, share of family labour used on the farm, rented land, and position in a less favoured area. After removing severe outliers for the production variables shown in Table 1, using the 25th and 75th percentile ± three times the interquartile range in each class, the resulting subset for this study contained 40,376 dairy farm enterprise observations. Stata 15.1 was used for the entire analysis.

6.3.3.2. Farm Classification

When assessing economic farm performance, it is important to compare and benchmark producers that operate under similar circumstances. In the context of efficiency analysis for example, different production frontiers, reflecting different production technologies, may apply to different sets of farms. Efficiencies of various producers need to be estimated with respect to the appropriate technology (Kumnhakar et al., 2015). Farming conditions and technological choices vary within and between countries. For context-specific data analysis, this heterogeneity requires some kind of classification or grouping. One simple option to address the issue is to estimate production frontiers and calculate economic performance indicators for distinct countries or regions. However, in production economics such a type of classification is generally considered arbitrary (Orea and Kumbhakar, 2004; Mekonnen et al., 2015).

Producers within the same region or country may operate under different production circumstances, whereas producers in different countries may be more similar and share a production frontier. For instance extensive grazing systems for dairy production can be found in Poland as well as in France or Austria. Latent differences are thus considered more important than a strict geographic categorisation or separating between conventional and organic farms in terms of estimating distinct production frontiers.

Following Orea and Kumbhakar (2004), we employed a latent class model to allocate dairy farms to groups that are characterised by a higher degree of homogeneity. Subsequently, profitability and efficiency were analysed. A similar approach had for example been used to examine efficiency of dairy farming in Spain (Alvarez and Corral, 2010) or to study the effects of innovation systems on eco-efficiency in agriculture (Mekonnen et al., 2015; Grovermann et al., 2019). To account for technological choice and key farm and agro-climatic characteristics, the class splitting model was specified using the following variables: Costs per dairy cow (labour, feed, forage, machinery, other direct costs), farm area, stocking density, forage and fodder areas, and average yearly minimum and maximum temperatures. Farms that possess similar attributes in the above variables are more likely to be in the same class[3]. Optimal class size was determined by applying the Schwarz Bayesian Information Criterion (SBIC) and the rule of no small classes (< than 5% of total observations). This rule has long been used in practice as a part of the idea of obtaining more useful results, but has recently been discovered to also have some theoretical justifications based on the posterior distribution of the class proportions (Nasserinejad et al., 2017). As the latent classes capture key production technology differences, organic and conventional dairy enterprises could be compared against a common frontier in each class.

6.3.3.3. Performance Measurement

The calculation of the gross margin outcome variable was performed using per cow revenue (without subsidies) and per cow variable cost figures. Cost items included in the calculation were labour, feed, forage, machinery maintenance and other costs, as specified in the Data section. The gross margin was then derived by simply subtracting variable costs from sales revenues. The efficiency scores of individual farms were estimated by applying the stochastic production frontier framework. This is a standard approach for the economic analysis of agricultural production systems with applications ranging from animal to crop production, from high-income to medium- and low-income economies and from farm-level to country-level analysis (for some recent examples see Houssain et al. 2012; Mekonnen et al., 2015 or Finger et al., 2018). A meta-study by Bravo-Ureta et al. (2007) comprised 167 farm level efficiency estimations of which the majority are based on stochastic frontier models, with nonparametric deterministic and parametric deterministic frontier models being other key estimation techniques found in the literature.

In this study we computed farm-specific efficiency scores using an output-oriented measure. This means that a farm is inefficient if a higher level of output is attainable for the given input

[3] For a more detailed explanation of the method, including the equations required for the assignment of observations to classes, see Orea and Kumbhakar (2004) or Grovermann et al. (2019).

use. Key specification decisions relate to the choice of the functional form of the production frontier and the distribution of the inefficiency term in the model. Stochastic frontier analysis distinguishes between a term that captures statistical noise and a term that accounts for inefficiency (Alvarez and Arias, 2014). As explained by Khumbhakar et al. (2015) assuming a half-normal distribution for the inefficiency term implies that the majority of the producers are operating at rather efficient levels. For the highly competitive dairy sector, this is considered an appropriate specification. For the estimation of the frontier model a Cobb-Douglas functional form was selected, as the test of the constant returns to scale assumption confirmed this specification in all four classes. Therefore, output is considered to increase in proportion with an increase in all production factors. Based on Orea and Kumbhakar (2004), the empirical latent class stochastic frontier model was thus parameterised as follows:

$$\ln(\mathrm{REV}_i)\,|_c = ß_0 + ß_i \ln(X_i)\,|_c + ßT + v_i\,|_c - u_i\,|_c \qquad (1)$$

where the vertical bars with index *c* mean that different models were separately estimated for each class *c*. The dependent variable REV_i measures milk revenues per dairy cow for farm *i* and class *c*. X_i constitutes a farm- and class specific vector of output-enhancing inputs, these being per cow land requirements, labour costs, feed costs, forage costs, machinery costs and other costs. *T* are dummies for the years 2012 and 2013 (2011 being the reference year). The systematic error component v_i is assumed to be an independently and identically distributed random error term with a normal distribution. The inefficiency term u_i is measured as the ratio of observed output to the corresponding class-specific stochastic frontier and follows in this application, as explained above, a half-normal distribution, taking on values between zero and 1.

6.3.3.4. Impact analysis

The focus of our interest is the impact of certification on the gross margin and efficiency scores of farms in each of the four classes. To obtain a valid measure of impact from the certification intervention some pre-processing of the data was needed to avoid the comparison being confounded with other factors (White and Raitzer, 2017). For a valid comparison, producers in the participating and non-participating groups should not significantly differ in characteristics that are not related to certification, but rather possess similar production conditions (such as agro-climatic circumstances) or farm traits (such as size or specialisation). Due to non-random assignment, a particular challenge when comparing certified to non-certified producers is self-selection bias, i.e. the fact that those producers that choose to participate in a standard often significantly differ in a number of characteristics from those producers that do not participate (Meemken and Qaim, 2018b; Ssebunya et al., 2018). Several techniques to control for such a bias are available, of which propensity score matching, reweighting or instrumental variable approaches, are among the most widely used (see reviews by Lopez-Avila et al, 2017 or Knook et al., 2018). While the latter can control for selection on properties that are often unobserved, such as entrepreneurship or risk behaviour for example, matching and reweighting methods rely on observable information, i.e. a dataset that captures all important variables that directly or indirectly determine selection. In the present analysis endogeneity due to unobserved properties can occur in some or all instances of the eight class-outcome combinations. Therefore, we employ an endogenous treatment model, using the *etregress* routine in Stata.

The model tests selection on unobservable characteristics and, where appropriate, corrects for such a bias (Fischer and Qaim, 2012; Tambo and Wünscher, 2014).

6.3.3.5. Endogenous treatment model

The core concept of the selected model is that the variation between predicted probabilities of treatment and actual treatment can be captured by adding terms in the outcome regression, which absorb the effects of unobservable determinants of treatment (White and Raitzer, 2017). First a binary participation variable is regressed on observable characteristics using a probit model. From this, two ancillary terms, the selection hazard rate and the inverse mills ratio, are predicted, which are then inserted in a linear regression determining the effect of participation on the outcome of interest. In that way, unbiased treatment effects can be estimated. Results of the endogenous treatment model are based on the premise that at least one valid instrument has been identified, i.e. an independent variable included in the probit model that influences participation, but not the outcome of interest. Based on observed differences in the data for three out of four classes, we postulate for three classes that dairy farms with fallow land are more likely to adopt organic certification, but that this is not associated with their performance. As information on fallow land was available in the dataset, it was decided to use this variable as an instrument in the estimation of the endogenous treatment model for classes one to three. Following Fischer and Qaim (2012) and Tambo and Wünscher (2014), the exogeneity of the instrument was tested by including it as an additional regressor in a 'placebo' regression model with explanatory variables X, using only data from non-certified farms. Fallows were not significantly associated with either gross margins or efficiency (see Tables A5 and A6 in the appendix for details).

The outcome equation of the endogenous treatment model was defined for each class *c* (as indicated by the vertical bars with index *c*) as follows:

$$\mathrm{PERF}_i |_c = ß_0 + ß_1(\mathrm{FARM1}_i) |_c + ß_2\mathrm{ORG}_i\lambda_{1i} |_c + ß_3(1\text{-}\mathrm{ORG}_i)\lambda_{0i} |_c + ß_4\mathrm{L} + ß_5 T + u_i |_c \qquad (2)$$

where $PERF_i$ represents the two performance outcome variables, gross margin and efficiency per farm *i*. A range of farm characteristics are captured by the vector $FARM1_i$: Farm size, economic size, stocking density, subsidy payments, farm assets, forage area, degree of specialisation, share of family labour, rented land, position in a less favoured area. Details on each variable are displayed in Table . Similar control variables have been used in other impact evaluation studies (Mayen et al. 2010; Läpple et al., 2012; Tambo and Wünscher, 2014). However, data on certain characteristics of the farm manager, such as age or education, was unavailable in our case. However, these properties are assumed to be implicit in the other variables or are captured by the added term that accounts for unobservables. The variable ORG is equal to one if a dairy enterprise possesses organic certification and zero otherwise. λ_{1i} (inverse mills ratio) and λ_{0i} (hazard rate) are parameters produced by the joint estimation of equations (2) and (3) in order to absorb the selection bias. Besides controlling for time lapse, heterogeneity between countries, e.g. due to differences in regulatory or support schemes, was accounted for in the model. Country and time fixed effects were included through location dummies L and T. Lastly, u_i is the random error term.

To remedy the potential endogeneity problem, the selected model estimates jointly with equation (2) an equation for the certification decision using the variable representing fallow land as instrument. The participation equation takes the following form:

$$\mathrm{ORG}_i |_c = \delta_0 + \delta_1 \ln(\mathrm{FARM2}_i) |_c + \delta_2 \mathrm{FAL}_i |_c + u_i |_c \quad (3)$$

where the binary dependent variable ORG_i captures the organic certification decision. The vector $FARM2_i$ contains the same variables as the vector *FARM1i* in the outcome equation, apart from stocking density and actual subsidies, which are considered to be somewhat influenced by organic farming rather than the other way around. The covariate FAL_i stands for the instrumental variable.

The Wald test for independent equations is used to support interpretation of the output of the endogenous treatment model. Where the test statistic is insignificant, indications are that there is no need to control for unobservable characteristics, thus matching or reweighting methods are sufficient. For this case, for estimating effects in class four and for better understanding the results overall, we therefore complemented the analysis with a balancing through entropy weights, a data pre-processing technique proposed by Hainmüller (2012) and implemented in Stata through the *ebalance* routine. A very similar approach was used by Meemken and Qaim (2018) to analyse the impact of food standards. Due to exact adjustment of covariate moments, it is considered an appealing alternative to standard matching or reweighting methods when estimating causal effects from observational studies (Zhao and Percival, 2015). Using entropy balancing, covariate balance for mean and variance moments could be directly incorporated in the estimation. Farm-specific weights were thus generated using the covariates in the vector $FARM2_i$. Including these weights in further analysis, differences correlated with selection and existing prior to or independent of treatment can be controlled or eliminated. Certification effects were estimated using a weighted regression for the gross margin and technical efficiency outcomes, based on the same outcome equation as specified for the endogenous treatment model (equation 2). We thus used a doubly robust approach as described by Hainmueller (2012). As weights are only assigned to untreated units in the comparison group (non-certified farms) through the data pre-processing, entropy balancing produces estimates of the average treatment effect on the treated (ATT) (Meemken and Qaim, 2018). This is comparable to the effect generated by the endogenous treatment model.

6.3.4. Results

6.3.4.1. Classification

The overall class splitting approach resulted in four distinct groupings, as shown in Table . This was considered suitable, with the smallest class including 11% of observations, whereas a five-class model would have produced a distinct minor class with less than 4% of observations. Class one represents dairy farming under cool conditions (including for example Scandinavian and Baltic farms), class two characterises more intensive dairy farming under temperate conditions (including for example many Dutch, German or Irish Farms), while class three characterises more extensive dairy farming under temperate conditions (including for example many Polish or Austrian farms), and class four relates to dairy farming under warm conditions (including for example many Italian or Spanish farms). While there is no strict geographic split, there are geographical tendencies, e.g. 73% of Italian farms are found in class four and almost

all Dutch farms were assigned to class two. However, farms that exhibit distinct features, such as mountain dairy enterprises in Italy for example, are not allocated to class four, but rather to classes one or three (for more information on the distributions of farms by country and class see Table A1 in the Appendix). To illustrate differences among farms that are organic certified or not, data in Table are further subdivided according to certification status.

Table 1: Class-specific average production and farm characteristics (SD in brackets)

	Class 1		*Class 2*		*Class 3*		*Class 4*	
Description	*Dairy farming under cool conditions*		*Dairy farming under temperate conditions*				*Dairy farming under warm conditions*	
			More intensive		*Less intensive*			
Organic certified	***NO***	***YES***	***NO***	***YES***	***NO***	***YES***	***NO***	***YES***
Farms (#)	4,279	931	20,616	812	8,863	391	4,392	92
Production data								
Revenues (€/cow)[1]	2,627.16	2,596.98	2,542.46	2,742.70	1,486.50	1,688.55	2,507.93	2,707.35
	(991.86)	(1,010.34)	(645.51)	(805.67)	(534.97)	(782.24)	(1,035.23)	(1,202.53)
Land (ha/cow)	2.16	2.80	1.10	1.32	1.02	1.65	0.54	0.94
	(1.92)	(2.42)	(0.66)	(0.66)	(0.72)	(1.00)	(0.62)	(1.17)
Labour (€/cow)	1,026.10	1,088.09	658.06	849.85	512.40	862.30	689.76	844.62
	(753.53)	(816.78)	(367.32)	(551.21)	(404.07)	(604.48)	(539.82)	(520.67)
Feed costs (€/cow)	1,174.64	1,033.29	776.25	854.25	440.34	354.50	1,235.06	1,309.69
	(573.98)	(690.77)	(377.93)	(603.33)	(207.79)	(193.11)	(578.66)	(742.27)
Forage costs (€/cow)[2]	96.37	39.91	164.99	73.29	91.90	36.73	68.87	57.27
	(96.74)	(55.18)	(82.25)	(51.86)	(58.41)	(34.77)	(80.64)	(80.51)
Mach. costs (€/cow)	216.16	251.41	167.45	216.84	82.46	142.48	70.96	49.76
	(163.06)	(200.76)	(99.62)	(125.03)	(69.64)	(109.42)	(75.46)	(45.53)
Other costs (€/cow)	347.40	378.34	360.87	406.22	105.87	137.87	178.09	143.87
	(256.65)	(292.29)	(180.81)	(205.93)	(77.74)	(94.43)	(145.91)	(121.84)
Min. temperature (C)	2.18	2.30	6.24	5.94	4.56	4.19	10.32	10.84
	(1.99)	(1.85)	(1.15)	(1.09)	(0.72)	(1.03)	(1.90)	(1.75)
Max. temperature (C)	9.72	10.26	13.92	13.41	12.52	12.57	19.29	19.98
	(2.27)	(2.28)	(1.60)	(1.50)	(1.13)	(1.32)	(1.89)	(1.67)
Farm characteristics data								
Farm size (ha)	187.36	112.14	169.55	163.33	36.58	38.24	33.21	51.31
	(401.04)	(173.35)	(369.16)	(261.31)	(81.86)	(44.87)	(45.50)	(51.63)
Econ. Size (ESU)	220.72	138.60	370.96	361.15	54.36	55.08	207.49	192.10
	(396.39)	(171.90)	(609.71)	(412.69)	(73.12)	(48.20)	(234.18)	(173.29)
Stocking d. (cows/ha)	1.11	0.87	2.02	1.44	2.08	1.20	9.65	3.35
	(0.68)	(0.44)	(0.88)	(0.45)	(1.62)	(0.48)	(59.65)	(2.73)
Subsidies (€/ha)	320.85	255.44	339.64	310.23	203.43	260.46	1,254.02	472.89
	(308.25)	(170.18)	(126.86)	(89.99)	(86.75)	(109.90)	(7,792.04)	(511.50)
Assets (€)	1,838.11	2,199.39	1,323.77	1,733.09	1,513.75	2,024.24	693.62	584.33
	(1,465.28)	(1,534.63)	(933.98)	(1,163.23)	(1,175.63)	(1,684.52)	(795.41)	(555.62)
Forage area (ha)	132.60	94.89	103.78	123.44	21.77	30.24	28.48	46.57
	(257.53)	(138.39)	(178.05)	(181.11)	(34.49)	(33.95)	(37.36)	(49.44)
Specialisation (prop.)	0.66	0.61	0.67	0.68	0.62	0.59	0.75	0.68
	(0.14)	(0.13)	(0.16)	(0.14)	(0.16)	(0.13)	(0.14)	(0.15)
Family labour (prop.)	0.79	0.88	0.85	0.79	0.97	0.95	0.91	0.81
	(0.32)	(0.23)	(0.26)	(0.26)	(0.11)	(0.17)	(0.18)	(0.28)
Renting land (Y/N)	0.88	0.86	0.93	0.97	0.71	0.76	0.76	0.59
	(0.32)	(0.35)	(0.25)	(0.18)	(0.45)	(0.43)	(0.43)	(0.50)
Less favoured (Y/N)	0.86	0.94	0.51	0.50	0.72	0.88	0.62	0.85
	(0.35)	(0.25)	(0.50)	(0.50)	(0.45)	(0.33)	(0.48)	(0.36)
Fallow (Y/N)	0.03	0.05	0.09	0.13	0.07	0.09	0.04	0.01
	(0.19)	(0.21)	(0.29)	(0.33)	(0.25)	(0.27)	(0.20)	(0.10)

[1] Milk sale revenues do not include subsidies; [2] Forage costs were estimated based on seed, fertiliser, and pesticide expenditures.

6.3.4.2. Efficiency scores

Our results show that across all four classes efficiency levels are high, peaking among the dairy farms in class two.

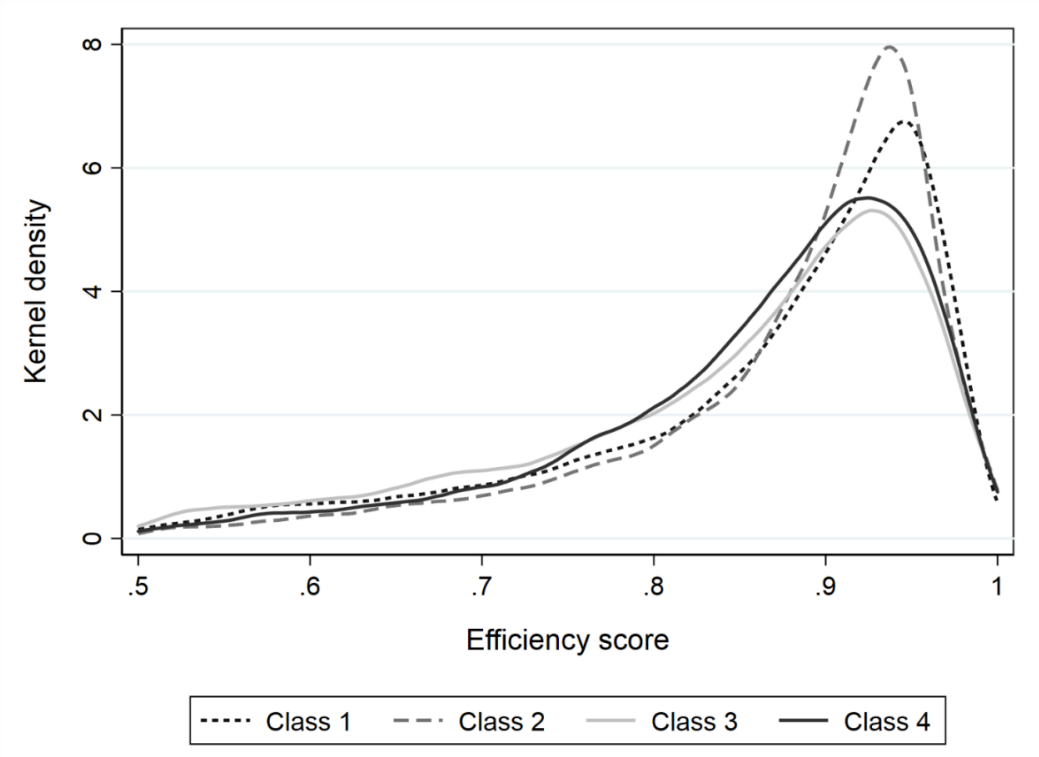

Figure 13: Distribution of efficiency scores in classes 1 to 4

From the first to the fourth class, average scores are 0.85, 0.87, 0.83 and 0.85 respectively. Distribution of efficiency scores are presented in Figure 1, revealing no huge differences among classes. Detailed regression outputs of the class-specific stochastic frontier estimations are provided in Table A2 in the appendix. All coefficients had the expected positive sign across the four classes, apart from those for land, where regression coefficients suggest mixed effects.

6.3.4.3. Certification impacts

The effects of organic certification vary among classes in terms of their magnitude, but are largely positive across all four classes. Certification impacts on profitability are highest among the more extensive central European farms in class three, with the estimated effect amounting to 70%. Profitability differences are less pronounced among the farms in cool northern European and intensive central European environments, being 38% in class one and 41% in class two (see Table 2). The results from the entropy balancing differ somewhat in terms of magnitude, but both estimation techniques show a similar trend. Due to the negative association between fallow and organic certification, the instrument was not found to be suitable for class four. Therefore, we rely only on the entropy balancing estimates in this case.

Contrary to the other classes, the findings for class four indicate no significant differences in terms of profitability, and neither for efficiency. For the other three classes, positive efficiency effects range from 3% to 5%. These relatively small estimated effects are predominantly due to the fact that the majority of all farms are operating at rather high efficiency levels.

Table 2: Certification impacts for profitability and efficiency outcomes across four classes

	Class 1		*Class 2*		*Class 3*		*Class 4*	
	GM (€/cow)	***EFF*** *(0-1)*	***GM*** (€/cow)	***EFF*** *(0-1)*	***GM*** (€/cow)	***EFF*** *(0-1)*	***GM*** (€/cow)	***EFF*** *(0-1)*
(1) Endogenous treatment model^								
ATT	128	0.032	169	0.043	172	0.028		
Sig.	ns	***	***	***	***	***		
Comparison	-288	0.849	409	0.869	244	0.834		
% change	44%	4%	41%	5%	70%	3%		
Wald test	ns	***	***	***	**	***		
(2) Entropy balancing model								
ATT	102	0.015	96	0.009	92	0.007	-18	0.001
Sig.	***	***	***	***	***	ns	ns	ns
Comparison	-273	0.835	410	0.879	113	0.829	247	0.865
% change	37%	2%	23%	1%	81%	1%	-7%	2%
N	5244		21,428		9,254		4,484	

Notes: ATT = Average Treatment Effect on the Treated; Comparison = Mean reference value in the comparison group; GM = Gross Margin; EFF = Efficiency; Wald test = Wald test of independent equations to test for selection on unobservable characteristics; *** = 1% significance level; **= 5% significance level; *= 10% significance level. ^Full regression outputs for the estimations of the endogenous treatment model are shown in tables A3 and A4 in the appendix.

According to our results, the endogenous treatment model is a reasonable choice for classes one to three for the estimation of treatment effects, with the exception of the profitability assessment in class one (for full model estimations, see Tables A3 and A4 in the appendix). As the Wald test of independent equations proved highly significant in five out of six estimations, the results of the endogenous treatment model are considered appropriate here. For the remaining case, where selection on unobservable characteristics appears to be no issue, results from the entropy balancing approach can be considered more appropriate. For class four, the entropy balancing approach was selected a priori, and no results from the endogenous treatment model are shown, as the instrument was found not to be suitable for this class and no other instrument was available. The low number of organic farms in this class would also render the application of the endogenous treatment model difficult. Augmenting the regression with additional terms would appear to produce less reliable results compared to cases with more treated units.

The per cow gross margin calculations indicate that several dairy enterprises are making a loss, as becomes also evident from the estimates in class one. In this context it is important to clarify that subsidies have not been taken into account in the computation of outcome

variables, as we intended to focus on 'pure' economic performance measures. While in the counterfactual analysis farms with organic certification appear slightly more efficient and considerably more profitable, in a simple comparison, as shown in Table 3, certified farms perform worse in terms of gross margin for classes two and three. This indicates that an impact evaluation approach produces results that differ substantially from a simple comparative approach. Therefore, an interpretation of the effects found here always needs to happen in the context of the method applied.

Table 3: Simple comparison (without any pre-processing)^ of certified and non-certified farms

	Class 1		*Class 2*		*Class 3*		*Class 4*	
Organic certified	***NO***	***YES***	***NO***	***YES***	***NO***	***YES***	***NO***	***YES***
Gross margin (€/cow)								
Mean	-233	-194	415	342	253	156	265	305
Standard dev.	(873)	(1030)	(604)	(682)	(590)	(709)	(789)	(626)
Sign. diff.	ns		***		***		***	
Efficiency								
Mean	0.85	0.86	0.87	0.89	0.83	0.87	0.85	0.87
Standard dev.	(0.12)	(0.12)	(0.11)	(0.09)	(0.13)	(0.14)	(0.12)	(0.11)
Sign. diff.	**		***		***		ns	

*** = 1% significance level; **= 5% significance level; *= 10% significance level. ^The simple comparison shown here does not involve the careful construction of a counterfactual and the balancing of properties among certified and uncertified dairy enterprises.

6.3.5. Discussion and Conclusions

Using a latent class counterfactual approach we were able to systematically quantify the economic impact of the organic standard for dairy farms across Europe. The study shows that certification pays off for those dairy farmers that converted to organic farming. This supports findings from previous more location-specific studies about the positive economic effects of organic certification (Bolwig et al., 2009; Hoop et al., 2017; Tran and Goto, 2019). In addition, findings indicate that not only were higher profits achieved on average, but small average efficiency gains also resulted from organic certification. The latter outcome is contrary to findings from previous studies that compared efficiency among organic and conventional dairy farms (Oude Lansink et al. 2002; Kumbhakar et al., 2009; Mayen et al., 2010). This might be explained by the fact that the present analysis relies on input and output variables being mostly expressed in monetary terms. Results may differ if for example milk yield was used instead of sales revenues as output variable. For the purposes of this study, it was decided to focus on financial returns that include price premiums for organic produce. Mayen et al. (2010) point out that efficiency estimates for certified farms are lower if a common frontier is assumed for organic and conventional farms. However, in the context of the present analysis, the choice was to focus on splitting classes using a latent class approach rather than estimating separate functions for organic and conventional farms or for specific geographic areas. Latent differences among farms are considered more central for addressing heterogeneity among farms than a priori defined categories. Certified dairy farms can rather easily substitute conventional inputs, and the categorical differences of organic vs. conventional production are thus not reflected in the classification, as it does not seem to be very decisive for defining the production frontier. This is an important aspect of latent class models: the resulting groups are entirely based on the statistical characteristics of the data with the aim to identify most distinct groups within the data, while all farms within a group transform economic inputs in a similar

way – as far as reflected in the data – into economic output. The opposite to this data-driven approach is to operate with predefined groups based on agronomically motivated cut-offs, such as production regions (e.g. plain, hills, mountains), production systems (organic vs. non-organic) or feed composition (e.g. grouped according to levels of concentrate feed shares in feeding rations). The advantage of such groups is that they are mutually exclusive along all single dimensions and make sense from an agronomic classification point of view – but may not reflect the "reality" regarding production technologies as captured in the input-output relations provided by the data analysed. The data-driven grouping on the other hand reflect economic input-output relations but may not be that easily given interpretation to from an agronomic point of view. Furthermore, they are not clear-cut and show overlaps along all dimensions.

Many organic dairy enterprises, just like conventional ones, can define and be very close to the class-specific frontiers, as our analysis revealed. A higher gross margin and economic efficiency of organic farms indicate that they succeed in using the same production conditions, contexts and means as conventional dairy farmers in the same group to achieve a slightly greater economic efficiency. According to the groups identified here, organic and conventional farms do not use different technologies, but they optimally exploit the same context to a different extent. Thus, improvements for those that underperform do not require a technology change but a number of adjustments to better operate within the option space provided by the current technology. It should be noted that our analysis focuses on efficiency per cow. Whilst the organic farms achieve greater economic performance per cow, due to the lower stocking rates within organic systems, the results per hectare of land may differ. Overall, the fact that high levels of efficiency can be found across all four classes, suggests that the scope for efficiency improvements under current conditions is rather restricted.

As in similar impact studies (Läpple et al., 2012; Tambo and Wünscher, 2014), the endogenous treatment model proved valuable in addressing selection bias by taking into account both observable and unobservable characteristics. The appropriate statistical test suggested that the correct model choice was made in five out of six estimations. For the remaining estimation and for class four estimations, as well as for checking the general direction of the effects, estimates from entropy balancing are provided. The overall approach, testing for selection on unobservables and otherwise using entropy balancing as data pre-processing method, follows the logic outlined by Meemken and Qaim (2018). The results of the endogenous treatment model are based on the premise that at least one valid instrument can be identified. Using fallow land as instrumental variable relies on the assumption that it is associated with deciding on organic certification, but not with the performance of dairy production. For three out of four classes, this is considered a valid assumption and was tested. For class four, other estimates were provided.

Overall, according to the results organic dairy production appears to be an economically sensible strategy for certified dairy farmers in Europe, with the exception of Mediterranean dairy enterprises. While certification might not be a viable option for several of the existing conventional farms, the results point out that non-certified farms with characteristics that are similar to those of the certified farms may benefit from conversion. The findings also show that higher dairy enterprise incomes are associated with higher efficiency.

An important factor to take into consideration when deriving from the present analysis any broader recommendation on transitioning to organic dairy farming is the consumer side. There have been signs that despite substantial recent growth, the potential of future organic dairy sales growth might limited due to market saturation. This implies a need for policy interventions to target the demand side, e.g. through attempting to include some external costs in the price of conventional milk. Following our results and economic reasoning, supply of sufficient organic dairy products seems less problematic, as financial incentives for conversion exist. An additional policy measure lies in the greening of conventional dairy production including fairer pricing. This might be a good alternative also for those farmers who do not consider organic certification as an option for their dairy enterprise. For future impact research on dairy farming, it would be of interest to extend the analysis beyond economic efficiency and profitability outcomes to include aspects of fair price, animal welfare and ecosystem services. Seufert et al. (2017) point out that environmental principles are inadequately represented by organic regulations. The concept of eco-efficiency might offer a promising indicator for studies that integrate the assessment of economic and environmental performance aspects.

6.3.6. References

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6.3.7. Appendix

Table A1: Distribution of farms by country and class

COUNTRY	Class 1	Class 2	Class 3	Class 4	Total
Austria	801	820	514	0	2,135
Belgium	0	958	5	0	963
Cyprus	0	0	0	22	22
Czech Republic	90	510	111	0	711
Denmark	1	1,116	0	0	1,117
Estonia	498	4	15	0	517
Finland	952	0	0	0	952
France	67	4,413	53	23	4,556
Germany	258	7,109	363	0	7,730
Greece	0	0	1	24	25
Hungary	0	209	38	9	256
Ireland	0	1,003	11	0	1,014
Italy	565	48	73	1,781	2,467
Latvia	877	21	246	0	1,144
Lithuania	290	50	596	0	936
Luxembourg	0	744	4	0	748
Malta	0	0	0	170	170
Netherlands	0	1,005	0	0	1,005
Poland	6	695	6,993	0	7,694
Portugal	0	10	16	505	531
Slovakia	68	113	14	2	197
Slovenia	7	492	154	5	658
Spain	0	337	43	1,941	2,321
Sweden	726	368	0	0	1,094
United Kingdom	4	1,403	4	2	1,413
Total	5,210	21,428	9,254	4,484	40,376

Table A2: Stochastic Frontier Analysis – Estimation results

	Class 1			Class 2			Class 3			Class 4		
VARIABLES	Coef.	SE	Sign	Coef.	SE	Sign	Coef.	SE	Sign	Coef.	SE	Sign
Land [ln(ha/cow)]	-0.070	0.009	***	-0.021	0.004	***	0.012	0.009		-0.011	0.007	
Labour [ln(hs/cow)]	0.107	0.006	***	0.053	0.003	***	0.039	0.007	***	0.216	0.008	***
Feed costs [ln(€/cow)]	0.256	0.008	***	0.189	0.004	***	0.243	0.007	***	0.367	0.012	***
Forage costs [ln(€/cow)]	0.001	0.001		0.013	0.002	***	0.061	0.004	***	0.004	0.002	**
Machinery costs [ln(€/cow)]	0.058	0.006	***	0.066	0.002	***	0.064	0.004	***	-0.010	0.004	**
Other var. costs [ln(€/cow)]	0.090	0.005	***	0.128	0.003	***	0.101	0.004	***	0.062	0.006	***
Constant	4.720	0.070	***	5.256	0.033	***	4.791	0.056	***	3.705	0.091	***
Observations	5,210			21,428			9,254			4,484		

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1; Dependent variable: Milk sales revenues [ln(€/cow)]

Table A3: Endogenous Treatment Model – Estimation results for gross margin outcome

GROSS MARGIN	Class 1			Class 2			Class 3		
EXPLANATORY VARIABLES	Coef.	SE	Sign	Coef.	SE	Sign	Coef.	SE	Sign
OUTCOME EQUATION									
Farm size [ln(ha)]	0.177	0.060	***	0.007	0.022		-0.014	0.025	
Economic size [ln(€)]	0.071	0.069		0.157	0.024	***	0.456	0.039	***
Stocking density [ln(cow/ha)]	0.648	0.059	***	0.456	0.022	***	0.206	0.027	***
Subsidies [ln(€/ha)]	-0.102	0.021	***	-0.033	0.009	***	0.033	0.020	*
Assets [ln(€/ha)]	0.050	0.010	***	0.102	0.006	***	0.062	0.006	***
Forage area [ln(ha)]	0.159	0.050	***	0.174	0.017	***	0.075	0.027	***
Specialisation [%]	1.206	0.106	***	0.541	0.033	***	0.700	0.041	***
Family labour (%)	0.877	0.060	***	0.758	0.025	***	1.040	0.062	***
Rented land [1=Yes]	0.143	0.035	***	0.066	0.015	***	0.016	0.010	
Less favoured area [1=yes]	-0.003	0.026		-0.054	0.008	***	-0.037	0.010	***
Permanent grassland [1=yes]	0.007	0.053		-0.071	0.020	***	-0.056	0.026	**
Organic certification [1=yes]	0.128	0.055	**	0.169	0.034	***	0.172	0.037	***
Constant	-2.680	0.190	***	-2.587	0.091	***	-3.811	0.159	***
PARTICIPATION EQUATION									
Farm size [ln(ha)]	-0.704	0.094	***	-0.724	0.074	***	-1.671	0.125	***
Economic size [ln(€)]	-0.181	0.038	***	-0.357	0.037	***	-0.224	0.062	***
Assets [ln(€/ha)]	0.161	0.026	***	0.307	0.030	***	0.192	0.031	***
Forage area [ln(ha)]	0.988	0.090	***	1.004	0.069	***	1.823	0.113	***
Specialisation [%]	-1.331	0.158	***	-0.380	0.132	***	-2.172	0.180	***
Family labour (%)	0.684	0.115	***	-0.734	0.094	***	-0.622	0.241	***
Rented land [1=Yes]	-0.061	0.067		0.269	0.084	***	0.050	0.062	
Less favoured area [1=yes]	0.233	0.081	***	-0.221	0.037	***	0.229	0.073	***
Fallow [1=yes]	0.200	0.111	*	0.160	0.052	***	0.010	0.008	*
Constant	-2.178	0.283	***	-2.292	0.298	***	-0.311	0.391	
Observations	5,210			21,428			9,254		
Wald test for indp. equations						***			**

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1;

Table A4: Endogenous Treatment Model – Estimation results for efficiency outcome

EFFICIENCY	Class 1			Class 2			Class 3		
EXPLANATORY VARIABLES	Coef.	SE	Sign	Coef.	SE	Sign	Coef.	SE	Sign
OUTCOME EQUATION									
Farm size [ln(ha)]	0.090	0.006	***	0.029	0.003	***	0.050	0.004	***
Economic size [ln(€)]	0.024	0.008	***	0.044	0.003	***	0.110	0.007	***
Stocking density [ln(cow/ha)]	0.011	0.007		0.034	0.003	***	-0.009	0.005	*
Subsidies [ln(€/ha)]	0.004	0.002	*	0.009	0.001	***	-0.011	0.003	***
Assets [ln(€/ha)]	0.023	0.002	***	0.032	0.001	***	0.022	0.001	***
Forage area [ln(ha)]	-0.068	0.007	***	-0.024	0.002	***	-0.081	0.005	***
Specialisation [%]	0.414	0.013	***	0.204	0.005	***	0.439	0.007	***
Family labour (%)	0.029	0.007	***	0.034	0.003	***	0.115	0.008	***
Rented land [1=Yes]	0.021	0.004	***	0.009	0.002	***	0.007	0.002	***
Less favoured area [1=yes]	-0.023	0.004	***	-0.022	0.001	***	-0.022	0.002	***
Permanent grassland [1=yes]	0.016	0.008	**	-0.006	0.003	**	0.014	0.005	***
Organic certification [1=yes]	0.032	0.007	***	0.043	0.006	***	0.028	0.006	***
Constant	0.254	0.024	***	0.214	0.013	***	0.189	0.023	***
PARTICIPATION EQUATION									
Farm size [ln(ha)]	-0.701	0.094	***	-0.720	0.074	***	-1.694	0.128	***
Economic size [ln(€)]	-0.177	0.039	***	-0.339	0.037	***	-0.243	0.063	***
Assets [ln(€/ha)]	0.173	0.030	***	0.332	0.035	***	0.205	0.033	***
Forage area [ln(ha)]	0.985	0.089	***	0.991	0.069	***	1.851	0.117	***
Specialisation [%]	-1.327	0.157	***	-0.327	0.137	**	-2.147	0.182	***
Family labour (%)	0.694	0.117	***	-0.721	0.095	***	-0.635	0.241	***
Rented land [1=Yes]	-0.061	0.067		0.278	0.084	***	0.055	0.063	
Less favoured area [1=yes]	0.225	0.080	***	-0.229	0.038	***	0.232	0.074	***
Fallow [1=yes]	0.203	0.105	*	0.157	0.052	***	0.016	0.107	
Constant	-0.701	0.094	***	-0.720	0.074	***	-1.694	0.128	***
Observations	5,210			21,428			9,254		
Wald test for indp. equations			***			***			***

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1;

Table A5: Placebo Model – Estimation results for gross margin outcome

GROSS MARGIN	Class 1			Class 2			Class 3		
EXPLANATORY VARIABLES	Coef.	SE	Sign	Coef.	SE	Sign	Coef.	SE	Sign
Farm size [ln(ha)]	0.213	0.063	***	-0.002	0.022		-0.028	0.025	
Economic size [ln(€)]	0.005	0.075		0.156	0.024	***	0.458	0.039	***
Stocking density [ln(cow/ha)]	0.679	0.064	***	0.456	0.022	***	0.209	0.027	***
Subsidies [ln(€/ha)]	-0.095	0.022	***	-0.035	0.010	***	0.035	0.020	*
Assets [ln(€/ha)]	0.049	0.011	***	0.101	0.006	***	0.061	0.006	***
Forage area [ln(ha)]	0.164	0.053	***	0.185	0.017	***	0.087	0.027	***
Specialisation [%]	1.262	0.117	***	0.518	0.033	***	0.685	0.041	***
Family labour (%)	0.821	0.062	***	0.757	0.026	***	1.060	0.065	***
Rented land [1=Yes]	0.150	0.038	***	0.067	0.015	***	0.016	0.010	
Less favoured area [1=yes]	0.033	0.027		-0.051	0.008	***	-0.039	0.010	***
Permanent grassland [1=yes]	0.058	0.059		-0.068	0.020	***	-0.061	0.026	**
Long-term fallow [1=yes]	-0.092	0.064		-0.012	0.013		-0.031	0.021	
Constant	-2.653	0.205	***	-2.555	0.093	***	-3.857	0.164	***
Observations	4,279			20,616			8,863		
R-squared	0.411			0.391			0.540		

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1;

Table A6: Placebo Model – Estimation results for efficiency outcome

GROSS MARGIN	Class 1			Class 2			Class 3		
EXPLANATORY VARIABLES	Coef.	SE	Sign	Coef.	SE	Sign	Coef.	SE	Sign
Farm size [ln(ha)]	0.086	0.006	***	0.028	0.003	***	0.050	0.004	***
Economic size [ln(€)]	0.033	0.009	***	0.043	0.003	***	0.114	0.007	***
Stocking density [ln(cow/ha)]	0.003	0.008		0.035	0.003	***	-0.010	0.005	**
Subsidies [ln(€/ha)]	0.004	0.003		0.009	0.001	***	-0.012	0.003	***
Assets [ln(€/ha)]	0.023	0.002	***	0.032	0.001	***	0.022	0.001	***
Forage area [ln(ha)]	-0.073	0.007	***	-0.021	0.002	***	-0.083	0.005	***
Specialisation [%]	0.419	0.014	***	0.201	0.005	***	0.442	0.007	***
Family labour (%)	0.031	0.007	***	0.034	0.003	***	0.113	0.008	***
Rented land [1=Yes]	0.024	0.005	***	0.009	0.002	***	0.007	0.002	***
Less favoured area [1=yes]	-0.019	0.004	***	-0.022	0.001	***	-0.022	0.002	***
Permanent grassland [1=yes]	0.009	0.009		-0.006	0.003	**	0.017	0.005	***
Long-term fallow [1=yes]	-0.002	0.004		-0.002	0.001		-0.003	0.003	
Constant	0.234	0.026	***	0.215	0.014	***	0.202	0.024	***
Observations	4,279			20,616			8,863		
R-squared	0.674			0.640			0.695		

Note: Significance levels: *** p<0.01, ** p<0.05, * p<0.1;