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Principal component and multivariate factor analysis of detailed sheep milk fatty acid profile

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Comparison between principal components and multivariate factor analysis to investigate
 detailed milk fatty acid profile in sheep.

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ABSTRACT

11 The fatty acid profile is one of the most important aspects of the nutritional properties of milk. 12 Fatty acid content in milk is affected by several factors as diet, physiology, environment, and genetics. 13 Recently, Principal Component Analysis (PCA) and Multivariate Factor Analysis (MFA) have been 14 used to summarize the complex correlation pattern of the milk fatty acid profile by extracting a 15 reduced number of new variables. In this work, the milk fatty acid profile of a sample of 993 Sarda 16 breed ewes was analysed with PCA and MFA in order to compare the ability of these two multivariate 17 statistical techniques in investigating the possible existence of latent substructures, and in studying 18 the influence of physiological and environmental effects on the new extracted variables. Individual 19 scores of PCA and MFA were analyzed with a mixed model that included the fixed effects of parity, 20 days in milking, lambing month, type of lambing, altitude of flock location, and the random effect of 21 flock nested within altitude. Both techniques extracted the same number of new variables (9) 22 explaining 80% of the total variance. In general, PCA structures were difficult to interpret, with only 23 four PC being associated to a clear meaning. PC1 in particular was the easier to interpret and agreed 24 with the interpretation of the first factor, being both associated to the FA of mammary origin. On the 25 other hand, MFA was able to identify a clear structure of all the extracted latent variables, confirming 26 the ability of this technique, to group FA according to their function or metabolic origin. Key

27 pathways of the milk FA metabolism were identified, as mammary gland *de novo* synthesis, ruminal 28 biohydrogenation, desaturation performed by SCD enzyme, and rumen microbial activity, confirming 29 previous findings in sheep and in other species. Generally, the new extracted variables were mainly 30 affected by physiological factors as DIM, parity and lambing-month; the type of lambing had no 31 effect on the new variables, altitude influenced only one PC and factor. Both techniques were able to 32 summarize a larger amount of the original variance into a reduced number of variables. Moreover, 33 factor analysis conformed its ability in identifying latent common factors clearly related to fatty acid 34 metabolic pathways.

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36 Keyword: fatty acids, principal components, factor analysis,

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INTRODUCTION

39 The interest of the scientific community and of the consumers in the nutritional and health-40 related properties of milk and dairy products has increased over the last decades. Strategies for 41 improving the milk content of some categories of fatty acids (FA) considered beneficial for human 42 health, as PUFA and CLA, have been developed. Most of them rely on feeding management, (Dewhurst et al., 2006; Toral et al., 2010; Nudda et al., 2014) being the diet one of the most important 43 44 factors affecting milk FA profile (Nudda et al., 2014). However, other factors such as genetics (Carta 45 et al., 2008; Correddu et al., 2019), physiology (De La Fuente et al., 2009), and environment (Sevi et al., 2002) can affect milk FA composition. 46

The elucidation of FA metabolic pathways and the knowledge of factors affecting their regulation are of great interest for improving milk nutritional properties. In particular, the complex phenotypic and genetic correlation pattern existing among individual milk FA hampers the modification of FA profile via feeding and genetic strategies (Cecchinato et al., 2019). Dimensionreduction multivariate statistical methods have been suggested for investigating such a complex correlation network. In particular, principal components analysis (**PCA**) (Fievez et al., 2003; Kadegowda et al., 2008) and Multivariate Factor Analysis (MFA) (Conte et al., 2016; Mele et al.,
2016; Correddu et al., 2017; Palombo et al., 2020) have been used to highlight common metabolic
pathways of FA in ruminant species.

56 Being both based on the factorization of the covariance or correlation matrix, and on the representation of the multivariate system with a lower number of new variables, PCA and MFA 57 58 appear somewhat similar. However, the way the factorization is carried out differs between the two 59 techniques. PCA is a model-free approach and it is mostly aimed at compressing the variance of the 60 system. PCA is particularly useful when few PC can explain large portion of the variance. On the 61 other hand, MFA starts from a model of the covariance structure of the multivariate system. In 62 particular, the factor model assumes that the covariance of a system could be partitioned in a 63 component shared by all the variables (communality) plus a component specific of each variable 64 (uniqueness). MFA aims at investigating the covariance structure and, in particular, at identifying 65 common latent variables (factors) that generate the quota of shared covariance among the original variables (Krzanowski, 2000; Morrison, 1976). In other words, PCA is more focused on the 66 observations whereas MFA is on the variables, respectively. 67

PCA of cattle milk FA composition was able to assess the relationship between individual milk FA and diet-induced milk fat depression (Kadegowda et al., 2008), and to investigate metabolic relationships among milk FA and to describe their origin (Fievez et al., 2003). PCA has been also used to analyze meat FA profile to differentiate lamb meat according to their origin (Díaz et al., 2005), and to study the relationship between quality traits of carcass and meat of light lamb (Caneque et al., 2014). MFA was successfully used to elucidate relationship between milk FA in dairy cows (Mele et al., 2016; Conte et al., 2016), Sheep (Palombo et al., 2020), and buffaloes (Correddu et al., 2017).

The use of the two methods on the same data may provide different and complementary results. In a study of cattle lactation curve traits, for example, PCA was able to extract from the correlation matrix of test day records two new variables related to the whole lactation and to the shape of lactation curve, respectively. On the same data, MFA generates two latent factors related to the
first and the second part of lactation, respectively (Macciotta et al., 2006).

80 The aim of this work was to compare results of the use of MFA and PCA in the analysis of 81 milk FA profile in sheep, in order to assess their ability to investigate the complex correlation pattern 82 that exists among these variables.

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MATERIALS AND METHODS

85 Animals and milk samples

The study was carried out on individual milk samples of 993 Sarda dairy ewes farmed in 48 flocks located in the island of Sardinia (Italy). Individual milk samples (one per sheep) were collected from April to July 2014, during the morning milking, by the Provincial Association of Animal Breeders (APA). FA profile of the milk samples was measured using gas chromatography (GC) as previously described (Correddu et al., 2017).

91 Statistical analysis

Data for a total of 49 individual FA were analyzed with PCA and MFA using SAS PRINCOMP and FACTOR procedures, respectively (SAS Inst. Inc., Cary, NC). The number of principal components (PC) to retain was defined according to the amount of explained variance (\geq 80%). In MFA, the number of factors to be extracted was based on their eigenvalue (>1), on their readability in terms of relationships with the original variables and biological meaning, and on the amount of explained variance. Factor interpretation was improved through a VARIMAX rotation.

Individual principal component and factor scores for each ewe were calculated and thenanalyzed with the following mixed linear model:

 $y_{ijklmno} = \mu + PAR_j + DIM_k + LM_l + LT_m + ALT_n + F(ALT)_o + e_{ijklmno}$

101	where $y_{ijklmnop}$ was the principal component or factor score; <i>PAR</i> is the fixed effect of the <i>j</i> -th parity
102	class (eight classes from 1 to >7); DIM is the fixed effect the <i>k</i> -th days in milking interval (five
103	intervals: < 110, 110 to 140, 141 to 170, 171 to 200, >200); LM is the fixed effect of the <i>l</i> -th class of
104	lambing month (1: January; 2: February and March; 3: October and November; 4: December); LT, is
105	the fixed effect of the the m -th type of lambing (two classes: single and multiple birth); ALT, is the
106	fixed effect of the <i>n</i> -th altitude of location of flocks (mountain > 500 mt above the sea level; hill \leq
107	500 and \geq 200 m a.s.l; plain < 200 m a.s.l.). Finally, <i>F</i> (<i>ALT</i>) is the random effect of the <i>o</i> -th flock
108	nested within altitude of location; and $e_{ijklmno}$ is the residual term. No effect of the date of the test was
109	included in the model because in most of flocks all samples were collected in the same day.
110	
111	RESULTS AND DISCUSSION
112	Descriptive statistics of detailed milk FA composition of the 993 samples of sheep milk are
113	reported in Supplementary Table 1.
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the paper of Correddu et al. (2016), respectively. This is a consequence of the different number of original variables considered (49 and 21, respectively). The larger number of original variables, and therefore of extracted PC (equal to the number of original variables), resulted in the partition of the total variance on a larger number of eigenvalues.

The analysis of eigenvector structure is a way for assigning a meaning to the extracted PC in terms of relationship with the original variables. In the present study, the interpretation of the extracted PC on the basis of their eigenvectors (Table 1) was rather difficult. Considering a threshold of ≥ 0.20 (absolute value), half of the FA exhibited coefficients exceeding this value in at least two/three different PC, whereas four FA showed no loading>0.20 for any extracted PCA (Table 1). This was particularly true for PC4, PC5, PC7, and PC9. An interpretation was attempted for the other PCs.

138 The first PC (PC1) presented highest loadings for most of the short and medium chain FA 139 (negatives), on some iso FA, C18:1cis-9 and long chain saturated FA (positives). Most of these FA 140 are totally or partially synthetized in the mammary gland (Chilliard et al., 2000). Therefore, PC1 141 could be considered an index of the activity of this organ. The PC2 had high negative loadings on 142 anteisoC13, C14:0, C16:0, C14:1cis-9, C16:1cis-9, C18:3n-6 and positives on some 143 biohydrogenation products and C18:3n-3. The association with FA of different origin and metabolic 144 pathways does not allow to assign a clear meaning to this PC. The only feature shared by FA 145 associated to this PC is their relationship with diet quality, especially with the use of grazing. In dairy 146 cattle (Fievez et al., 2003) the two first PC were mostly associated to FA belonging to four groups. 147 Two included FA that originate in the mammary gland from *de novo* synthesis or desaturase activity; 148 the other two consists of FA produced in the rumen from the biohydrogenation activity or from 149 microbial synthesis.

The PC3 presented high positive loadings for C15:0 and C17:0, and negative for several positional isomers of trans C18:1 and on C181*cis*-12, respectively. This PC could be related to the FA biohydrogenation processes occurring in the rumen (Shingfield et al., 2010). The PC3 had also 153 high loadings on some FA of microbial origin. The OBCFA profile has been proposed as useful tool 154 to predict shifts in microbial population associated in particular with the diet (Vlaeminck et al., 2006). PC6 showed the largest loadings for PUFAn-3, C18:2n-6, C18:1trans-11, and C18:2cis-9,trans-11, 155 156 i.e., the substrates (the first two) and products (the last two) of the ruminal FA biohydrogenation. Thus, based also on the opposite loading sign for substrates and products, PC6 could be considered 157 158 as an indicator of PUFA runnial biohydrogenation activity. The PC8 had large positive loadings on 159 C14:0, C18:1*trans*-4, 18:1*trans*-16+*cis*-14, and negative on C16:1*trans*-9, C18:1*trans*-11, C18:2*n*-6, 160 C18:2*cis*-9,*trans*-11, C20:3*n*-6 and C20:4*n*-6 (negatives). Considering the high loadings exhibited by 161 PUFAn-6 and by the main products of the biohydrogenation of C18:2n-6 (C18:1trans-11 and 162 C18:2*cis*-9,*trans*-11), this PCA could be interpreted as an indicator of PUFA*n*-6 in the diet.

163

164 *Factor analysis*

165 The suitability of the data set to the theoretical assumptions of the MFA was assessed through 166 the calculation of the Kaiser Measure of Sampling Adequacy (Kaiser MSA). This index estimates the 167 decrease of partial correlations compared to Pearson correlations between the observed variables. In 168 the present work, the MSA parameter was 0.75, close to the value of 0.80 indicated as the optimal 169 threshold for the suitability of a dataset to MFA (Cerny and Kaiser, 1977). This result was similar to 170 previous reports on the use of MFA on milk FA profile (Mele et al., 2016; Correddu et al., 2017). 171 Nine factors able to explain about 80% of the total variance of the system were extracted (Table 2). 172 The pattern of explained variance across the different factors was smoother compared to PC (Table 173 1).

The communality of original variables was on average 0.81 (\pm 0.11), similar to the value reported for buffaloes (0.79) (Correddu et al., 2017) and higher than in cattle (0.69) (Conte et al., 2016; Mele et al., 2016). to 0.96 (for C10:0), The two FA with the lowest value of communality (0.54 for C18:2*trans*-9,*trans*-12 and C18:3*n*-6) were the same reported in a work on buffaloes (C18:2*trans*-9,*trans*-12 and C18:3*n*-6). Therefore in both species these two FA are characterised by about 50% of independent variation. Largest communalities, in agreement with previous studies, have
been found for short and medium chain saturated FA (e.g.: C6:0, C8:0, C10:0, C12:0), associated to
the first or second latent factor. The high values observed for these FA, and the agreement among
studies, confirm that the variability of these FA is mostly related to a unique metabolic pathway,
similar among species.

The adequateness of the factor model for fitting the FA correlation matrix was confirmed by the simple structure of the rotated pattern (Morrison, 1976). In particular, each factor showed large loadings with few variables and small loadings with the other variables (Table 2), respectively. Each variable had a large loading in only one factor, with only one exception (C16:0). In total, 42 out of 49 FA exhibited a loading value ≥ 0.60 , considered as an empirical threshold for declaring a variable associated to a factor (Macciotta et al., 2015).

190 The first latent factor (F1) was positively correlated with short and medium chain FA (apart 191 from C4:0 and C16:0) and negatively with C18:1cis-9 and some long chain saturated FA (C20:0, 192 C22:0 and C24:0). Thus, it was considered an index of "mammary gland activity". A peculiarity of 193 F1 is its structural similarity with PC1. A concordance between the results of the first PC and the first 194 factor extracted from the same data set was observed in a study on body conformation traits in cows 195 (Olasege et al., 2019). F1 structure partially agrees with previous studies where it was associated to 196 mammary gland ability to maintain an optimal milk fat fluidity and to the FA neosynthesis (Conte et 197 al., 2016; Correddu et al., 2017; Palombo et al., 2020). The negative loadings of F1 for long chain 198 saturated FA (C20:0, C22:0 and C24:0) was not observed in previous studies. In a recent investigation 199 on Comisana sheep, they were associated to a factor interpreted as 'Branched fatty acids metabolism' 200 (Palombo et al., 2020). In cows they were associated to a different factor together with other saturated 201 and unsaturated LCFA (Conte et al. 2016; Mele et al., 2016), whereas in buffaloes they characterized 202 a specific factor (Correddu et al., 2017).

Being positively associated to the odd, iso, and anteiso FA (except iso C13:0), F2 was named
"OBCFA". These FA are almost completely synthesized by rumen microorganisms (Vlaeminck et

205 al., 2006). This result is in agreement with a previous report on sheep (Palombo et al., 2020), whereas 206 two distinct factors associated with OCFA and BCFA were found in cattle and buffaloes (Conte et al. 207 2016; Correddu et al., 2017). The relative milk concentration of these FA depends on the composition 208 of the microbial population (Vlaemink et al., 2006). The diet, especially its forage to concentrate 209 ratio, is one of the main factors affecting the relative abundance of microbial populations. Thus, 210 feeding management could affect the proportions of OCFA and BCFA in milk. Sheep involved in the 211 present study are farmed in the typical Mediterranean semi-extensive systems with pasture as main 212 feeding source (Macciotta et al., 1999; Molle et al., 2007). Under these conditions, forage to 213 concentrate ratio in the diet should be approximately similar in the various flocks and, therefore, also 214 the rumen microbial composition to a certain extent. As consequence, the correlation pattern of all 215 OBCFA is similar, and the underling pathway of variation is summarized in one unique latent factor. 216 Factor three and four were positively associated with all isomers of C18:1 and C18:2 217 originating from the ruminal biohydrogenation (BH) of PUFA, with the exception of C18:1trans-11 218 (vaccenic acid) and C18:2cis-9,trans-11 (rumenic acid). In particular F3 was associated with trans isomer of C18:1 from the 4th to the 10th position, C18:1*cis*-12 and, to a lesser extent, to C18:2*trans*-219 9,trans-12. F4 was associated with trans isomer of C18:1 from the 13th to the 16th position, C18:2cis-220 221 9,trans-12, C18:2cis-9,trans-13 and C18:3cis-9,cis-12,cis-15 (C18:3n-3, α-linolenic acid, LNA). 222 Although it is very difficult to unequivocally ascertain the metabolic origin of a specific minor BH 223 intermediate (Shingfield et al., 2010), the separation of these FA into two different latent factors can 224 suggest different metabolic pathways underling the BH of PUFA. In particular, FA associated to the 3th factor are often produced in the rumen during the BH process of C18:2*cis*-9,*cis*-12 (C18:2*n*-6, 225 226 linoleic acid) (Shingfield et al., 2010). This result is in agreement with a previous report in cattle 227 where an association of C18:2n-6 and its intermediate products in the same latent factor was found 228 (Mele et al., 2016). In the present study C18:2cis-9,cis-12 was not associated to F3 and, consequently, 229 we decide to assign the generic name of "biohydrogenation". Considering the association of C18:3n-230 3 and of some its ruminal BH intermediates with the F4, this factor was named "LNA-BH". Almost all FA here found to be associated to F3 and F4 were found in a single latent factor, together with
vaccenic and rumenic acids, in previous studies on cattle, buffalo and sheep (Conte et al., 2016;
Correddu et al., 2017; Palombo et al., 2020).

234 The fifth latent factor was named "desaturase", being positively associated with some products of Stearoyl Coenzyme-A Desaturase (SCD) activity (C12:1cis-9, C14:1cis-9, C16:1cis-9 235 236 and C17:1*cis*-9) and negatively with the preferred substrate of this enzyme (C18:0). The other SCD products, C18:1*cis*-9 and C18:2*cis*-9,*trans*-11, were highly correlated with the 1st and 7th latent 237 238 factors, respectively. This result is in agreement with previous investigations in buffaloes (Correddu 239 et al., 2017) and, partially, in cattle (Conte et al., 2016, Mele et al., 2016), where the C17:1cis-9 was 240 not associated with the factor related to SCD activity, but with the same factor including C18:1cis-9. 241 Results of the present study are also in partial agreement with a previous report in sheep (Palombo et 242 la., 2020). However, in this study the C17:1*cis*-9 did not correlated with any factor. Interestingly, 243 desaturase factor presented high loading value for C4:0 (-0.63), differently to previous studies where 244 this FA was associated to a factor with C6:0 (Mele et al., 2016), or was not associated with any factor 245 (Conte et al., 2016; Correddu et al., 2017).

246 Factor six was named CLA as it showed large correlations with C18:2cis-9,trans-11 (rumenic 247 acid) and C18:1trans-11 (vaccenic acid). It was associated to synthesis of the most abundant and 248 important milk CLA isomer (C18:2*cis*-9,*trans*-11) operated by the SCD in mammary gland. Rumenic 249 and vaccenic acids are of great importance for the nutritional quality of milk (Banni et al., 2003) and 250 many researches have been aimed to find strategies for increasing their concentration (Chilliard et al., 251 2001; Nudda et al., 2014). High CLA factor scores indicate milk characterized by high nutritional 252 value, probably related to sheep grazing high quality pasture. The partition of the SCD products into 253 three different factors is in agreement with the work of Mele et al. (2016), which explained this result 254 with the chain length and the unsaturation degree of the substrate on SCD activity. Conversely, 255 rumenic and vaccenic acids were associated to the biohydrogenation factor in Comisana sheep 256 (Palombo et al. (2020). In the present study also C16:1trans-9 was correlated to the CLA factor. A

similar result, even though to e lesser extent, was reported in Mele et al. (2016). In another work, it
was correlated with the factor associated to the LCFA (Conte et al., 2016).

The seventh and eighth latent factors were named "n-3" and "n-6" as they were positively 259 260 correlated with FA of the PUFAn-3 family and of the PUFAn-6 family, respectively. The extraction of two different factors for PUFAn-3 and n-6 is in agreement with recent report of buffaloes 261 262 (Correddu et al., 2017), whereas in cattle they were associated to a unique latent factor (Conte et al., 2016; Mele et al., 2016). This result could arise from differences in the metabolism of these FA, in 263 264 particular to the capacity to promote C18:3n-3 and C18:2n-6 elongation, or to differences in the dietary concentration of these two FA (Correddu et al., 2016). Although their milk concentration is 265 266 not high (0.5% of total FA, n-3 + n-6 excluding C18:3n-3 and C18:2n-6), these FA have great 267 nutritional importance (Connor, 2000). In particular high concentrations of PUFA along with a low n-6 to n-3 ratio is considered important for good health and normal development in humans 268 269 (Simopoulos, 2002). The ninth factor explained the 3% of the total variance and did not showed 270 significant loading values.

271

272 Mixed model analysis

273 Results of the mixed-model analysis carried out on the individual scores of the nine PC and 274 of the nine extracted factors are reported in Table 3.

275

276 Principal components

On average, the contribution of the flock to the PC variance was around 46%, with the highest values exhibited by PC3 (69%) and the lowest by PC8 (31%). The high contribution of the flock to the variance of PC3 could arise from the great influence of environmental factors as diet, climate and farming practices on ruminal microbial environment (Henderson et al., 2015), which, in turn, influences FA biohydrogenation process and the production of OBCFA. For similar reasons a low contribution of flock for the PC8 variance was not expected, being this PC interpreted as an indicatorof PUFA*n*-6 in the diet.

The DIM class significantly affected e PC1, PC2, and PC9 (Table 3). LS means of PC1 scores exhibited an increasing trend across lactation stages (Figure 2). This trend underlines a reduction in de novo FA synthesis as the lactation proceeds (they have negative loadings) together with an increase of C18:1*cis*-9 synthesis, in agreement with the reports of Timmen and Patton (1988). The same trend could be observed for PC9, even if the loadings of this PC were very lower compared to PC1. PC2 showed an opposite pattern (Figure 2).

290 Parity affected significantly PC1, PC5, PC6, and PC8. First lambing ewes exhibited the largest 291 LSmean of PC1 scores (Table 4), that was statistically different from later parities. The PC5 scores 292 decreased across parities, even if with some fluctuations. Scores of PC6 decreased from the 1st to the 5th parity and then increased till the 7th; whereas PC8 showed the opposite behavior (Table 4). 293 Interestingly, the effect of parity on PC6 underline a high concentration of both n-3 and n-6 PUFA in 294 295 primiparous sheep, followed by a decrease in the intermediate parities and then by an increase in the 296 last parities. Similarly to other milk composition traits, FA are affected by parity due to changes in 297 energy and overall metabolism of the ewes as the lactation number proceeds (González-García et al., 298 2015). Results of the present study partially agree with previous researches that found higher 299 proportions of more desirable FA in milk of first-parity compared to later parities both in sheep and 300 cows. (Mierlita et al., 2011; Bilal et al., 2014). The larger content of favorable FA especially in first 301 parity animals is conformed also pattern of PC8 scores (Table 4).

The lambing month significantly affected PC1, PC5, PC6, and PC9. Scores for all these PC, except from PC6 (Figure 3), were negative from October to December and positive from January to March. PC1 exhibited larger absolute values in comparison to PC5 and PC9. Altitude of location of flock affected only PC9 scores, with a decreasing trend passing from plain to mountain. The lambing type did not affect any of the 9 PC.

308 Latent factors

309 Results of the mixed-model analysis factor scores are reported in Table 3. On average, the 310 contribution of the flock effect to the total variance was 45%, with the highest values for the n-3311 (55%) and the lowest for the *desaturase* (25%) factors, respectively. This finding is consistent with 312 the larger effect of environmental and management factors on the milk content of FA arising from 313 the diet (i.e. PUFA) compared to those of endogen production (i.e.: MUFA produced by delta-9 314 desaturase) (Stoop et al., 2008; Correddu et al., 2019). According to the high value observed for PC3, 315 the *OBCFA* and *biohydrogenation* factors exhibited high values of variance explained by the flock 316 effect (0.49 and 0.53, respectively).

317 Lambing type and the altitude of flock location did not affect any of the extracted factors. 318 The DIM significantly affected mammary activity, OBCFA, LNA-BH, desaturase, and CLA factor 319 scores. In particular least squares means for scores of mammary activity, LNA-BH, and CLA 320 decreased along the lactation, whereas OBCFA and desaturase exhibited an opposite trend (Figure 321 4). The effect of DIM class on the mammary activity factor confirmed results obtained for PC1. The 322 higher contents of de novo FA and lower of C18:1cis-9 in early compared to late lactation evidenced 323 by F1 pattern (Figure 4) are in agreement with previous reports in buffaloes (Correddu et al., 2017). 324 On dairy cows a different behavior was observed (Conte et al., 2016; Mele et al., 2016). Such 325 differences could be partially ascribed to differences in the metabolism among species, even if the 326 data distribution along the lactation should be also considered. In the typical Mediterranean sheep 327 farming system, the milk of the first month of lactation is suckled by the lamb. Thus, milk tests 328 considered in the present work were available only from 45 days after parturition, The lack of data 329 for the first month could have therefore hampered the modeling of a trend of FA metabolic pathway 330 in early lactation. Lactation patterns of LNA-BH and CLA factors evidenced a trend similar to 331 mammary gland activity. Such a decreasing pattern underlined a higher activity of LNA ruminal 332 biohydrogenation and of CLA synthesis (due to the increase of SCD substrate, C18:1trans-11) in the 333 first part of lactation compared to the last part. This finding was in agreement to that observed for the

PC2, and it could be explained by the high content of C18:3n-3 in spring Mediterranean pastures 334 335 (Cabiddu et al., 2005), that tends to decrease as in late spring-summer. The pattern of the Desaturase 336 factor underlines an increasing SCD activity as the lactation proceeds, as observed in cattle and 337 buffaloes (Mele et al., 2016; Correddu et al., 2017). According to Mele et al. (2016), the increasing 338 trend of OBCFA factor along the lactation can be related to the variation of forage to concentrate 339 ratio. An higher amount of concentrate is usually provided in early lactation to meet energy needs of the animals; as the lactation proceeds, there is an increase of the proportion of forages in the diet 340 341 resulting an increase of FA produced by the ruminal microorganism, in particular by cellulolytic 342 bacteria (Vlaemink et al., 2006). Higher scores for BCFA factor were observed in cows fed a diet 343 with higher percentage of forage (Conte et al., 2016).

344 Parity had significant effect on mammary activity, OBCFA, n-3, and n-6. Mammary activity 345 exhibited an increasing trend from 1st to third parity (Table 5) and then decreased till the eight parity. *OBCFA* scores were rather constant from the 1st to the 4th parity and then rapidly decrease in the 7th 346 and 8^{th} parities. The *n*-3 and *n*-6 factors showed a similar waving pattern (Table 5). There is a lack of 347 348 consensus on the effect parity on latent factors extracted from milk FA. Some works evidenced a 349 large effect (Mele et al., 2016), others minor or no effect (Conte et al., 2016; Correddu et al., 2017). 350 The effect of parity on milk FA is mainly due to the larger PUFA content in primiparous compared 351 to pluriparous animals, that exhibit higher amount of SFA. These figures have been observed both in 352 cows and sheep (Mierlita et al., 2011; Bilal et al., 2014). Differences between parities in the extent of 353 tissue mobilization and in the content of FA synthase in the mammary gland, as well as the rumen microflora, can partially explain the effect of parity on milk FA (Miller et al., 2006; Friggens et al., 354 355 2007). In the present work, first lambing animals exhibited lower scores for mammary activity, and 356 higher for n-3 and n-6 factors, respectively. Scores of the OBCFA factor underlined a decreasing 357 pattern of ruminal derived FA with age, as previously reported in cows and buffaloes (Mele et al., 358 2016; Correddu et al., 2017).

The month of lambing influenced significantly (P<0.05) all the latent factors, except from *desaturase* and *n-3. Mammary activity*, *LNA-BH*, and *CLA* factors exhibited positive scores for lambings occurring from October to December and negative scores for those from January to March, respectively (Figure 3). An opposite trend could be observed for *OBCFA*, *biohydrogenation*, and *n*-6. Sheep lambing is strictly seasonal, thus the evaluation of the effect of lambing month on a productive response has a different meaning in comparison, for example, with dairy cattle.

365 In the typical farming system of Sarda sheep there is a confounding between lambing season, 366 production season, and parity. Pluriparous ewes lamb in late fall-early winter, whereas first parity 367 animals lamb in late winter-early spring. All the animals are then dried off at the beginning of 368 summer. As a consequence, the number of autumn lambing ewes is larger, and they have also longer 369 lactations. Autumn lambing sheep were sampled in late-lactation, whereas winter lambing sheep were 370 sampled in mid-lactation. Thus, the effects on FA profile of the physiological condition of the animal 371 (stage of lactation, parity) and of the environment (mainly pasture quality) on the FA profile are 372 difficult to disentangle. For example, the larger scores for mammary activity found in autumn lambing sheep reflect the higher activity of mammary gland in the FA synthesis in late lactation, whereas 373 374 winter lambing sheep showed higher content of FA derived from body reserve mobilization in early 375 lactation to meet energy requirement. The lower scores of LNA-BH and CLA factors observed in milk 376 of sheep lambing in winter underlines a lower activity of rumen LNA biohydrogenation, that result 377 in low milk contents of alpha-linolenic acid, its biohydrogenation intermediates, C18:1trans-11 and 378 C18:2*cis*-9,*trans*-11. This pattern reflects, probably, the lower quality of pastures in late spring 379 compared to late-winter early-spring. This finding has interesting implications on the quality of milk 380 in relationship to the season of lambing and to the availability of high-quality pasture, evidencing 381 higher content of desired FA in milk of sheep lambed in autumn.

382

383 **Comparison of the two techniques**

The comparison of the two different dimension-reduction methods for analyzing the FA profile of sheep milk provided interesting insights for assessing the usefulness of these two multivariate techniques in deciphering complex correlation patterns and in generating new phenotypes that could be further used for management or genetic purposes.

The continuous development of analytical technology has remarkably increased the number 388 389 of potentially detectable FA. Thus, the number of original variables investigated in the present 390 research was larger in comparison with studies carried out some years ago. In many cases, the newly 391 measured FA were probably not distinguishable from other FA in the previous analyses. Instead of 392 being a simple addition of new variables, this increase of system dimensionality may have added 393 further complexity to the correlation structure of FA. Both PCA and MFA were able to summarize 394 the 49 dimensions of the original multivariate system with 9 new axis that accounted for about 80% 395 of the original variance. Some authors suggest that, when the number of original variables is large, 396 PC and factors tend to coincide (Schneeweis and Mathes, 1995). However, in the present study, some 397 differences have been found in the meaning of the extracted variables.

398 In general, PCA structures were difficult to interpret, also in comparison with previous 399 researches on milk FA profile. On the other hand, in spite of the large number of starting variables, 400 MFA was able to identify through the factor pattern rotation a clear structure of the extracted latent 401 variables. In particular, it was confirmed the ability of this technique, to group FA according to their 402 function or metabolic origin. In agreement with previous works carried out also in other ruminant 403 species, MFA identified key pathways of the milk FA metabolism, as mammary gland de novo 404 synthesis, ruminal biohydrogenation, desaturation performed by SCD enzyme, and rumen microbial 405 activity, that control a relevant quota (80%) of the complex correlation pattern among individual FA. 406 Some partial concordances between the two techniques have been observed. Both PC1 and F1 407 were related to the FA of mammary origin, and the correlation between their scores (Table 6) was 408 rather large (about -0.80). A latent variable related to mammary gland activity able to explain the 409 largest amount of variance was obtained also in other studies (Mele et al., 2016; Palombo et al., 2020).

410 These results suggest to hypothesize a role of main driving force in regulating milk FA (co)variance 411 pattern for mammary FA synthesis pathway. Other large correlations were observed between F9 and 412 PC9 (-0.87), Biohydrogenation factor and PC3 (-0.76), n-3 factor and PC7 (-0.66). This amount of 413 covariation among principal components and factors arise from the fact that both techniques start 414 from the factorization of the correlation matrix. On the other hand, differences still remain due to the 415 different assumptions on the covariance of the system. This fact, together with the possibility of 416 rotating the factor pattern to improve its interpretation, provides more power to the MFA in 417 identifying the real dimensions of milk FA profile system.

PCA confirmed its ability in reducing the dimension of the system, but it was not able to efficiently discriminate observations. It has to be considered that the animal sample of the present study was taken from commercial flocks where no specific experimental treatments were applied. Previous studies where PCA was able to distinguish clusters of observations were usually feeding trials where experimental diets aimed at modifying milk FA composition were tested. These treatments may have therefore enhanced differences between animals and emphasised the clustering of observations in the PC space.

A major criticism to MFA is for the indeterminacy of its solutions and for the lack of robustness against outliers (Wang et al., 2017). However, it should be pointed out that the various studies on the use of MFA for analysing milk FA, carried out in different species, and under different experimental conditions, led to very similar results. Such a consistency across studies could be considered as a proof for the adequacy of the MFA model to fit the covariance structure of milk FA composition.

Individual scores of latent factors extracted from the correlation matrix of FA were able to discriminate cows farmed in herds with different feeding management (Mele et la., 2016). They could be therefore used as synthetic indicators of milk FA metabolism for management purposes. Moreover, genetic parameters of latent factors have been estimated in dairy cattle (Cecchinato et al., 2019). Some latent variables, as the one related to the activity of the SCD factor, showed moderate heritability (0.31), thus suggesting a possible use of factor scores as novel phenotypes in breeding plans. Instead
of being considered simple traits, factor scores should be regarded as aggregate phenotypes and their
inclusion as breeding goals should be aimed at improving milk nutritional quality through the
modification of specific metabolic pathways.

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CONCLUSIONS

443 The two multivariate statistical techniques used in this study were able to efficiently summarize 444 the milk FA profile of sheep with a reduced number of new variables. However, due to the partitioning 445 of the variance in a large number of extracted variables, PCA was not able to distinguish stratification 446 in the considered sample of animals. On the other hand, the multivariate factor analysis revealed the 447 existence of latent factors controlling the correlation pattern of milk fatty acids. In particular, some 448 independent factors were associated to metabolic pathways involved in the synthesis and modification 449 of milk FA, both in the mammary gland and in the rumen. Moreover, essential FA of dietary origin 450 (PUFAn-3 and PUFAn-6) were associated to two independent factors, confirming the diet as 451 important factor in affecting milk FA profile. The results of the mixed linear model showed a weak 452 influence of the fixed effects on the extracted factors. The clear meaning of the extracted latent factors 453 suggest to hypothesise a possible role as novel phenotypes for breeding and management purposes.

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Descrizione	Mean	SD	CV(%)	Min	Max
C4:0	2.67	0.37	13.83	1.52	4.05
C6:0	1.75	0.37	21.02	0.46	2.65
C8:0	1.60	0.46	28.46	0.28	2.84
C10:0	5.52	1.76	31.86	0.87	10.18
C10:1	0.02	0.01	51.71	0.00	0.06
C11:0	0.25	0.09	34.30	0.05	0.65
C12:0	3.48	1.00	28.78	1.08	8.15
iso C13:0	0.03	0.01	34.04	0.01	0.08
C12:1	0.04	0.01	33.41	0.02	0.13
iso C14:0	0.13	0.04	33.41	0.04	0.33
C14:0	10.81	1.54	14.23	5.28	18.42
iso C15:0	0.31	0.07	23.79	0.11	0.66
anteiso C15:0	0.54	0.11	20.81	0.21	0.91
C14:1c9	0.20	0.08	42.43	0.04	0.68
C15:0	1.17	0.18	15.36	0.57	2.37
iso C16:0	0.34	0.07	20.73	0.08	0.65
C16:0	25.95	2.97	11.43	18.51	36.69
iso C17:0	0.44	0.09	19.99	0.14	0.80
C16:1 <i>trans</i> -9	0.20	0.10	48.97	0.06	0.73
anteiso C17:0	0.49	0.08	17.19	0.15	0.78
C16:1cis-9	0.89	0.26	29.01	0.41	2.30
C17:0	0.78	0.11	14.46	0.42	1.32
C17:1cis-9	0.23	0.06	25.30	0.11	0.61
C18:0	10.29	2.51	24.38	1.37	21.00
C18:1trans-4	0.02	0.01	49.99	0.00	0.16
C18:1 <i>trans</i> -5	0.02	0.01	53.52	0.00	0.12
C18:1 <i>trans</i> -6 + 8	0.23	0.11	49.45	0.07	1.10
C18:1 <i>trans</i> -9	0.27	0.08	31.56	0.13	0.91
C18:1trans-10	0.42	0.44	105.73	0.11	7.85
C18:1 <i>trans</i> -11	2.06	1.03	50.21	0.46	5.77
C18:1trans-13 + trans-14	0.86	0.45	51.90	0.22	4.74
C18:1c9	17.23	3.64	21.11	5.37	34.75
C18:1cis-12	0.31	0.13	40.17	0.11	1.07
C18:1 <i>trans</i> -16 + c14	0.50	0.15	29.34	0.12	1.08
C18:2trans-9,trans-12	0.02	0.01	63.00	0.01	0.18
C18:2cis-9,trans-13	0.44	0.17	38.08	0.14	1.64
C18:2cis-9,trans-12	0.15	0.03	23.38	0.07	0.34
C18:2n6	2.09	0.51	24.33	0.92	4.32
C20:0	0.32	0.12	39.19	0.04	1.36
C18:3n6	0.04	0.02	39.81	0.01	0.15
C18:3n3	0.89	0.50	55.76	0.20	3.35
C18:2cis-9,trans-11	1.03	0.47	45.52	0.28	3.16
C22:0	0.17	0.06	32.76	0.02	0.50
C20:3n6	0.03	0.01	29.32	0.01	0.07
C20:4n6	0.13	0.05	36.62	0.04	0.33
EPA	0.06	0.02	29.91	0.03	0.15
C24:0	0.08	0.03	40.23	0.00	0.19
DPA	0.13	0.03	27.05	0.04	0.28
DHA	0.04	0.02	38.70	0.01	0.12

Supplementary Table 1. Descriptive statistic for individual fatty acids in sheep fat milk (n = 993)

Table 1. Eigenvectors and eigenvalues of the first nine principal components extracted from the
 577 correlation matrix of the 49 Fatty acids.

				Principa	1 Compone	nt (PC)			
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
C4:0	-0.054	0.143	0.006	-0.205	0.123	0.041	-0.287	-0.160	0.099
C6:0	-0.219	0.039	0.119	-0.099	0.239	0.031	-0.036	-0.062	0.054
C8:0	-0.233	0.009	0.124	-0.033	0.237	0.011	0.052	-0.047	0.013
C10:0	-0.239	-0.044	0.124	0.015	0.216	-0.005	0.110	-0.006	0.036
C10:1	-0.189	-0.074	0.044	0.101	0.095	-0.035	0.103	0.116	0.005
C11:0	-0.201	-0.173	0.102	0.167	0.068	-0.010	0.042	0.056	-0.048
C12:0	-0.228	-0.094	0.109	0.068	0.190	-0.022	0.151	0.045	0.019
isoC13:0	0.192	0.019	0.113	-0.114	-0.042	-0.072	0.099	0.137	0.143
anteisoC13:0	-0.094	-0.246	0.071	0.217	-0.029	-0.051	0.096	0.181	-0.032
isoC14:0	0.198	-0.008	0.155	0.096	0.054	-0.100	-0.065	0.013	0.281
C14:0	-0.170	-0.206	0.092	0.005	0.011	-0.021	0.091	0.198	0.174
isoC15:0	0.210	0.044	0.134	0.030	0.024	-0.213	0.033	0.063	0.004
anteisoC15:0	0.090	0.128	0.198	0.193	0.101	-0.278	-0.057	0.041	-0.027
C14.1cis-9	-0.011	-0.288	-0.010	0.188	-0 199	-0.010	-0.022	0.172	-0.008
C15:0	0.019	0.049	0.224	0.275	0.040	-0.098	-0.019	0.110	0.146
isoC16.0	0.151	0.048	0.130	0.186	0.180	-0.137	-0.149	0.059	0.136
C16:0	0.038	-0.245	-0.001	-0.118	-0 199	0.087	-0.147	0.031	0.249
isoC17:0	0.030	0.035	-0.035	0.002	0.199	-0.131	0.147	0.025	-0.242
$C16:1trans_9$	-0.114	0.055	0.033	0.092	-0 202	-0.180	0.032	-0 311	0.147
anteisoC17.0	0.127	0.105	0.025	0.100	0.202	-0.100	-0.060	-0.014	-0.211
C16:1cis 0	0.127	-0 248	0.090	0.10/	-0.249	-0.140	-0.000	-0.014	0 103
C17:0	0.039	-0.240	-0.024	0.194	0.127	0.010	-0.108	0.050	-0.105
C17.0	0.120	0.052	0.212	0.203	0.127 0.147	0.120	0.000	0.014	0.037
C17.1018-9	0.155	-0.105	0.070	0.201	-0.147	0.052	-0.022	-0.085	-0.190
C10.0	0.155	0.191	-0.021	-0.212	0.100	-0.078	0.107	0.109	-0.138
C10.1 trans-4	0.090	0.030	-0.240	-0.041	0.107	-0.013	0.245	0.202	0.14/
C18:1trans-5 C18:1trans-6	0.054	0.027	-0.203	0.031	0.119	0.007	0.274	0.11/	0.185
C18: 1 trans-0+8	0.030	0.038	-0.344	0.100	0.000	-0.087	0.147	0.050	0.110
C18:Itrans-9	0.025	0.064	-0.339	0.107	0.002	-0.121	0.121	0.008	0.06/
C18:1trans-10	-0.007	-0.013	-0.245	0.194	0.086	-0.003	0.093	-0.066	0.131
C18:Itrans-11	-0.122	0.233	-0.033	0.104	-0.138	-0.214	0.081	-0.263	0.186
C18:1trans-13+t14	-0.154	0.216	-0.080	0.125	0.088	0.117	-0.154	0.156	0.001
C18:1cis-9	0.229	-0.018	-0.089	-0.012	-0.100	-0.030	-0.012	-0.059	-0.336
C18:1cis-12	0.071	-0.043	-0.294	0.095	0.126	0.089	-0.090	0.032	0.037
C18:1trans-16+cis-14	-0.090	0.284	-0.073	0.056	0.064	0.117	-0.160	0.210	-0.128
C18:2trans-9,trans-12	-0.030	0.013	-0.159	0.253	0.033	0.152	0.031	0.001	0.205
C18:2cis-9,trans-13	-0.139	0.162	-0.101	0.253	-0.091	0.119	-0.166	0.124	-0.174
C18:2cis-9trans-12	-0.087	0.192	-0.139	0.190	-0.012	0.143	-0.197	0.176	-0.121
C18:2n-6	0.093	-0.056	-0.063	0.149	0.133	0.312	-0.249	-0.268	0.134
C20:0	0.245	0.003	0.010	-0.020	-0.015	0.034	-0.018	0.157	0.172
C18:3n-6	0.020	-0.205	-0.001	0.076	0.193	0.118	-0.103	-0.150	0.125
C18:3n-3	-0.105	0.212	0.105	0.015	-0.150	0.289	-0.066	0.072	0.129
C18:2cis-9,trans-11	-0.111	0.150	-0.027	0.193	-0.267	-0.224	0.076	-0.306	0.085
C22:0	0.205	0.114	0.119	0.019	-0.070	0.102	-0.102	0.142	0.267
C20:3n-6	0.144	-0.121	-0.044	0.090	0.213	0.131	0.001	-0.280	0.027
C20:4n-6	0.153	-0.160	-0.019	0.064	0.193	0.141	0.059	-0.326	-0.077
EPA	-0.039	0.176	0.169	0.088	-0.104	0.259	0.277	-0.004	-0.028
C24:0	0.189	0.147	0.127	-0.002	-0.066	0.118	-0.070	0.092	0.205
DPA	0.090	0.137	0.150	0.064	-0.069	0.299	0.367	-0.072	-0.087
DHA	0.120	0.044	0.098	0.022	-0.052	0.313	0.346	-0.043	-0.081
eigenvalues	12.28	7.38	6.55	3.84	2.61	2.58	1.53	1.42	1.26
Var. explained (%)	25.06	15.06	13.37	7.83	5.32	5.27	3.13	2.89	2.57

Table 2. Rotated factor pattern and communality.

]	Factors ¹					Com ²
	F1	F2	F3	F4	F5	F6	F7	F8	F9	Com-
C12:0	0.95	-0.06	-0.11	0.03	0.06	0.02	-0.01	-0.06	<mark>-0.03</mark>	0.94
C10:0	0.95	-0.08	-0.19	0.06	-0.11	0.06	0.00	-0.06	<mark>-0.01</mark>	0.96
C8:0	0.87	-0.09	-0.24	0.12	-0.28	0.07	-0.01	-0.05	<mark>-0.03</mark>	0.93
C11:0	0.83	-0.05	-0.17	0.06	0.41	0.01	-0.08	0.03	<mark>-0.03</mark>	0.91
C6:0	0.77	-0.13	-0.29	0.14	-0.42	0.05	-0.05	-0.03	0.05	0.89
C10:1	0.73	-0.06	0.00	0.12	0.17	0.04	-0.05	-0.12	<mark>-0.01</mark>	0.59
C14:0	0.73	-0.17	-0.12	-0.17	0.35	-0.13	-0.11	-0.14	0.25	0.83
isoC13:0	-0.48	0.36	-0.08	-0.41	-0.08	-0.20	0.18	-0.18	<mark>0.17</mark>	0.68
C24:0	-0.58	0.45	-0.15	0.01	-0.18	-0.08	0.35	0.01	0.32	0.82
C22:0	-0.60	0.49	-0.11	-0.02	-0.10	-0.13	0.29	0.03	<mark>0.40</mark>	0.88
C20:0	-0.66	0.37	0.14	-0.25	0.02	-0.31	0.13	0.07	0.21	0.82
C18:1 <i>cis</i> -9	-0.79	0.10	0.11	-0.18	0.16	-0.18	0.02	0.10	<mark>-0.37</mark>	0.88
anteisoC15:0	-0.08	0.86	-0.19	0.01	-0.06	0.20	0.01	-0.14	<mark>-0.13</mark>	0.85
isoC16:0	-0.20	0.81	-0.03	-0.05	-0.02	-0.06	-0.04	0.16	0.06	0.73
anteisoC17:0	-0.15	0.80	0.02	0.12	-0.07	-0.01	0.04	0.14	<mark>-0.38</mark>	0.84
C15:0	0.19	0.72	-0.20	0.10	0.19	0.16	0.16	-0.03	<mark>0.14</mark>	0.72
isoC14:0	-0.35	0.69	-0.08	-0.33	0.06	-0.07	0.07	0.15	<mark>0.24</mark>	0.82
C17:0	-0.07	0.67	-0.16	-0.02	0.05	-0.10	0.48	0.22	0.03	0.76
isoC15:0	-0.47	0.66	-0.08	-0.34	-0.02	-0.07	0.07	-0.12	<mark>-0.07</mark>	0.81
isoC17:0	-0.48	0.53	0.26	-0.14	-0.05	-0.22	0.00	0.11	<mark>-0.37</mark>	0.80
C18:1 <i>trans</i> -6 + 8	-0.18	-0.12	0.89	0.14	0.00	0.10	-0.19	0.02	<mark>-0.08</mark>	0.92
C18:1trans-9	-0.23	-0.14	0.83	0.17	0.00	0.21	-0.21	-0.02	<mark>-0.13</mark>	0.90
C18:1trans-5	-0.13	-0.08	0.82	-0.02	-0.10	-0.08	0.03	0.00	0.02	0.71
C18:1trans-4	-0.27	-0.05	0.76	-0.08	-0.14	-0.21	0.01	-0.10	0.02	0.73
C18:1trans-10	0.04	-0.06	0.68	0.15	0.13	0.15	-0.11	0.25	<mark>-0.05</mark>	0.60
C18:1 <i>cis</i> -12	-0.25	-0.12	0.65	0.18	0.07	-0.20	-0.22	0.35	-0.05	0.75
C18:2trans-9,trans-12	0.11	0.00	0.49	0.34	0.19	0.13	0.08	0.29	0.15	0.54
C18:2cis-9,trans-13	0.16	-0.08	0.11	0.87	0.11	0.27	0.03	-0.06	<mark>-0.07</mark>	0.90
C18:2cis-9,trans-12	0.01	-0.04	0.22	0.86	-0.07	0.13	0.00	-0.03	-0.02	0.81
C18:1 <i>trans</i> -16 + cis-14	0.02	0.02	0.09	0.82	-0.41	0.08	0.08	-0.21	<mark>-0.03</mark>	0.91
C18:1trans-13 + trans-14	0.29	-0.03	0.14	0.80	-0.29	0.17	0.01	-0.09	0.07	0.86
C18:3 <i>n</i> -3	0.09	-0.11	-0.30	0.56	-0.23	0.21	0.43	-0.12	<mark>0.36</mark>	0.85
C14:1 <i>cis</i> -9	0.14	-0.08	0.02	-0.14	0.88	-0.16	-0.16	0.07	<mark>0.10</mark>	0.89
C16:1 <i>cis</i> -9	-0.14	-0.10	-0.07	-0.09	0.88	-0.05	-0.14	0.17	<mark>0.01</mark>	0.87
C12:1 <i>cis</i> -9	0.55	0.06	-0.02	-0.10	0.71	-0.12	-0.08	0.00	0.00	0.84
C17:1 <i>cis</i> -9	-0.30	0.35	-0.11	-0.04	0.62	0.02	0.18	0.28	<mark>-0.19</mark>	0.75
C18:0	-0.50	0.22	0.13	-0.10	-0.61	-0.23	0.13	-0.27	<mark>-0.23</mark>	0.89
C4:0	0.00	-0.14	-0.23	0.17	-0.63	0.07	-0.19	0.08	<mark>0.13</mark>	0.57
C18:2cis-9trans-11	0.08	0.00	0.04	0.22	0.09	0.92	-0.02	-0.17	<mark>-0.05</mark>	0.93
C16:1trans-9	0.10	0.02	-0.05	0.21	-0.17	0.88	0.07	-0.19	<mark>0.03</mark>	0.91
C18:1trans-11	0.13	0.03	0.11	0.25	-0.26	0.86	-0.01	-0.22	<mark>0.03</mark>	0.95
DPA	-0.20	0.17	-0.12	0.03	-0.08	0.04	0.88	0.03	<mark>-0.05</mark>	0.87
DHA	-0.25	0.07	-0.04	-0.11	0.02	-0.15	0.77	0.12	<mark>-0.03</mark>	0.71
EPA	0.11	0.09	-0.23	0.27	-0.10	0.20	0.75	-0.12	0.07	0.78
C18:2 <i>n</i> -6	-0.20	0.06	0.10	0.14	0.06	-0.13	0.06	0.80	<mark>0.13</mark>	0.76
C20:4 <i>n</i> -6	-0.18	0.12	0.12	-0.39	0.13	-0.25	0.13	0.67	<mark>-0.24</mark>	0.81
C20:3 <i>n</i> -6	-0.18	0.17	0.20	-0.28	0.07	-0.21	0.07	0.66	<mark>-0.13</mark>	0.68
C18:3 <i>n</i> -6	0.21	0.03	0.04	-0.22	0.20	-0.25	-0.12	0.56	<mark>0.07</mark>	0.54
C16:0	-0.05	-0.07	-0.04	-0.04	0.06	0.00	-0.07	0.04	<mark>0.42</mark>	0.75
Eigenvalue	8.92	5.47	4.79	4.74	4.70	3.47	3.04	2.81	1.53	
Var. explained (%)	17.62	10.80	9.46	9.36	9.29	6.86	6.00	5.54	3.01	

- ¹ F1 = Mammary activity; F2 = OBCFA; F3= Biohydrogenation; F4 = LNA (alpha-linolenic acid) BH; F5 = Desaturase; F6 = CLA; F7 = n-3; F8 = n-6; F9 = C16. ² Communality.
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					P-value			- Elook (zono)
	item		DIM	Parity	Lambing-month	Lambing-type	Altitude	– Flock (zone)
	Princip	oal components						
	PC1		<0.001	<0.001	<0.001	0.683	0.469	0.53
	PC2		<0.001	0.647	0.413	0.213	0.831	0.53
	PC3		0.762	0.635	0.249	0.267	0.545	0.69
	PC4		0.067	0.157	0.072	0.934	0.407	0.36
	PC5		0.195	0.008	0.006	0.177	0.343	0.42
	PC6		0.153	0.006	0.029	0.744	0.526	0.51
	PC7		0.187	0.180	0.469	0.079	0.156	0.39
	PC8		0.186	0.018	0.691	0.209	0.938	0.31
	PC9		0.032	0.688	<0.001	0.337	0.042	0.37
	Latent	factors ¹						
	F1	mammary activity	<0.001	0.022	<0.001	0.860	0.921	0.43
	F2	OBCFA	<0.001	<0.001	<0.001	0.559	0.907	0.49
	F3	biohydrogenation	0.137	0.800	0.025	0.486	0.596	0.53
	F4	LNA-BH	<0.001	0.588	<0.001	0.059	0.222	0.39
	F5	desaturase	<0.001	0.614	0.143	0.187	0.425	0.25
	F6	CLA	<0.001	0.209	0.002	0.350	0.583	0.40
	F7	n-3	0.062	0.001	0.213	0.140	0.445	0.55
	F8	<i>n-6</i>	0.122	0.007	<0.001	0.901	0.501	0.50
	F9	<u>C16</u>	<mark>0.004</mark>	<mark>0.500</mark>	<mark>0.016</mark>	<mark>0.175</mark>	<mark>0.031</mark>	0.52
587 588 589 590 591 592	¹ Floe ² <i>OB</i> bioh 3 far	ck(zone) = contribute of <i>CFA</i> = odd and brand ydrogenation; <i>CLA</i> = of nily; <i>n-6</i> = polyunsatu	of flock nester ched-chain fa conjugated lin rated fatty aci	d within alti tty acids; <i>L</i> oleic acids; ds belongin	tude of location to NA-BH = alpha-lir n-3 = polyunsatura g to the omega-6 fa	the total varianc nolenic acid (C1 ated fatty acids be amily; $C16 = pa$	e; 8:3 <i>cis-9,ci</i> . elonging to Ilmitic acid	s-12, <i>cis</i> -15) the omega- (C16:0).
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Table 3. Effect of DIM, parity, month and type of lambing, and altitude of flock on the 9 principal
 components (PC) and 9 latent factors (F)

moniter		Principal c	omponent	
parity –	PC1	PC5*	PC6	PC8
1	$1.98^{a} \pm 0.45$	0.54±0.21	$0.29^{a} \pm 0.23$	$-0.09^{ab} \pm 0.15$
2	$0.60^{b} \pm 0.45$	0.30±0.21	0.03 ^{ab} ±0.23	$0.10^{ab} \pm 0.16$
3	$0.30^{b} \pm 0.44$	0.44 ± 0.21	$-0.26^{ab}\pm0.23$	$0.08^{ab} \pm 0.15$
4	$0.53^{b} \pm 0.44$	0.34 ± 0.20	$-0.27^{b}\pm0.23$	$0.27^{a}\pm0.15$
5	$0.47^{b} \pm 0.45$	0.28±0.21	$-0.28^{ab}\pm0.23$	$0.07^{ab} \pm 0.16$
6	$0.42^{b}\pm0.46$	0.02 ± 0.22	$-0.03^{ab} \pm 0.24$	$-0.04^{ab} \pm 0.16$
7	$0.56^{b} \pm 0.49$	-0.03±0.24	$0.16^{ab} \pm 0.26$	$-0.20^{b}\pm0.18$
8	$0.49^{ab} \pm 0.64$	-0.35±0.32	$-0.17^{ab} \pm 0.34$	$-0.32^{ab}\pm0.26$

Table 4. Least square means (± standard error) of the principal components affected by parity.

 $\overline{a,b,c}$ least square means with different superscript letters within a column differ (P<0.05) *although PC5 was significantly affect by parity, differences among contrasts did not reach the

607 statistical significance ($\alpha = 0.05$).

Table 5. Least square means (± standard error) of the latent factors affected by parity

pority		Latent fac	ctors	
parity	mammary activity	OBCFA	n-3	n-6
1	$-0.37^{b}\pm0.13$	$0.23^{ab} \pm 0.14$	$0.09^{ab} \pm 0.14$	0.35 ^a ±0.14
2	-0.06 ^{ab} ±0.13	$0.15^{ab} \pm 0.15$	$-0.03^{abc} \pm 0.14$	$0.11^{ab} \pm 0.14$
3	$0.04^{a}\pm0.13$	$0.23^{a} \pm 0.14$	$-0.24^{c}\pm0.14$	$0.08^{ab} \pm 0.13$
4	-0.04 ^{ab} ±0.13	$0.21^{a}\pm0.14$	$-0.21^{bc} \pm 0.14$	$-0.07^{b}\pm0.13$
5	-0.08 ^{ab} ±0.13	$0.08^{abc} \pm 0.15$	$-0.15^{abc} \pm 0.14$	$-0.05^{b}\pm0.14$
6	$-0.10^{ab}\pm0.14$	$-0.01^{abc} \pm 0.15$	$0.05^{a} \pm 0.15$	$0.01^{ab} \pm 0.14$
7	$-0.16^{ab}\pm0.15$	$-0.15^{bc} \pm 0.16$	$0.06^{abc} \pm 0.16$	$0.15^{ab} \pm 0.15$
8	$-0.29^{ab} \pm 0.20$	$-0.45^{c}\pm0.21$	$-0.14^{abc} \pm 0.20$	$-0.01^{ab} \pm 0.20$

 $\overline{a,b,c}$, least square means with different superscript letters within a column differ (P<0.05)

Ta	ble 6 Co	rrelation	matrix bet	ween the s	scores of p	rincipal c	omponent	s and later	nt factors	
		PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
F Ma	actor1	-0.78	-0.25	0.24	0.16	0.43	-0.03	0.23	0.05	0.11
		< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.3976	< 0.0001	0.1532	0.0008
F O	actor2 BCFA	0.41	0.21	0.45	0.51	0.37	-0.36	-0.07	0.18	0.13
		< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.0276	< 0.0001	< 0.0001
F	actor3 BH	0.12	0.04	-0.76	0.25	0.25	-0.09	0.42	0.16	0.26
		0.0002	0.2467	< 0.0001	< 0.0001	< 0.0001	0.0067	< 0.0001	< 0.0001	< 0.0001
F Ll	actor4 NA BH	-0.32	0.50	-0.20	0.40	-0.05	0.35	-0.43	0.30	-0.23
		< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.1463	< 0.0001	< 0.0001	< 0.0001	< 0.0001
F De	esaturas	0.03	-0.61	0.01	0.55	-0.51	-0.01	0.04	0.20	-0.13
	•	0.3162	< 0.0001	0.7817	< 0.0001	< 0.0001	0.8356	0.234	< 0.0001	< 0.0001
F	actor6 CLA	-0.26	0.37	-0.02	0.29	-0.42	-0.36	0.11	-0.60	0.22
		< 0.0001	< 0.0001	0.5706	< 0.0001	< 0.0001	< 0.0001	0.0008	< 0.0001	< 0.0001
F	actor7 N3	0.14	0.26	0.31	0.12	-0.12	0.59	0.66	-0.03	-0.05
		< 0.0001	< 0.0001	< 0.0001	0.0001	0.0003	< 0.0001	< 0.0001	0.3595	0.1358
F	actor8 N6	0.18	-0.27	-0.10	0.28	0.34	0.45	-0.31	-0.62	0.12
		< 0.0001	< 0.0001	0.0021	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	0.0001
F	actor9	-0.04	-0.01	0.11	-0.09	-0.23	0.24	-0.20	0.26	0.87
		0.2497	0.671	0.0004	0.0072	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Table 6 Correlation matrix between the scores of principal components and latent factor

621 Figure Captions	621	Figure	Captions
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- **Figure 1.** Plots of the scores for the first two principal components (PC1 and PC2) of animals
- belonging to different class of DIM (from 1 to 5 in figure 1A and averaged in mid and late lactation
- 626 in figure 2B).
- **Figure 2.** Classes of days in milk (DIM) pattern of PC1, PC2 and PC9.
- **Figure 3.** Effect of lambing month on PC1, PC5, PC6 and PC9.
- 629 Figure 4. Classes of days in milk (DIM) pattern of mammary activity, OBCFA, LNA-BH,
- *Desaturase* and *CLA* factors.
- 631 Figure 5. Effect of lambing month on *mammary activity*, OBCFA, biohydrogenation, LNA-BH,
- *CLA* and n-6 factors.



638 639 640 641 Correddu. Figure 2.

















