The use of seemingly unrelated regression to predict in vivo the carcass composition of lambs

Vasco Cadavez

Mountain Research Center (CIMO)
ESA - Instituto Politécnico de Bragança
Bragança, Portugal
e-mail: vcadavez@ipb.pt

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Outline

Carcass quality

Good quality carcasses

- Reduced amount of fat
- But enough fat to guarantee: Good presentation and Protect the meat

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Carcasses value

- A carcass with an optimum composition: Highest price
- Composition moves away from the optimum: Value should suffer depreciation

Carcass classification

Aims of classification

- Base for fair payments
- Communication with consumers’

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Classification systems

- Accurate
- Based on simple models
- Predict muscle proportion (not muscle weight)

Published work

Common feature of published work

- Predict lean meat weight or lean meat proportion
- Several independent equations are estimated separately by ordinary least squares (OLS)
- Assumption of independence is not supported
    - Biological knowledge
    - Carcass compositional traits are correlated both phenotypically and genotypically
    - The equations for predicting carcass compositional traits are interrelated
    - Single-equation approach is inefficient from a statistical point of view

Multiple equations models

Set of equations

1. Set of equations sharing a common error structure with non-zero covariance is said to be contemporaneously correlated
2. Seemingly Unrelated Regression (SUR) estimator
    - Accounts for these contemporaneous correlations
    - Allows the p dependent variables to have different sets of explanatory variables
    - SUR method estimates the parameters of all equations simultaneously
    - Greater efficiency of the parameter estimates

Objectives

1. To compare alternative models for simultaneously predicting carcass compositional traits

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2. To compare the efficiency of the OLS and SUR estimators

Animals

- 125 lambs - Churra Galega Bragançana
  - 82 males
  - 43 females

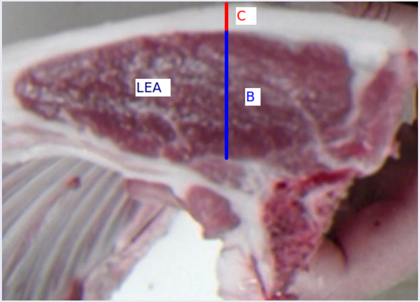
Slaughtering

- Carcasses weighted - HCW
- Carcasses were cooled at 4ºC for 24h
- Left side dissected
  - Lean meat proportion (LMP)
  - Subcutaneous fat proportion (SFP)
  - Intermuscular fat proportion (IFP)
  - Bone plus remainder proportion (BP)
  - Kidney and knob channel fat proportion (KCFP)

Tissues thickness measurements

Subcutaneous fat thickness

- C12: 12^{th} and 13^{th} ribs



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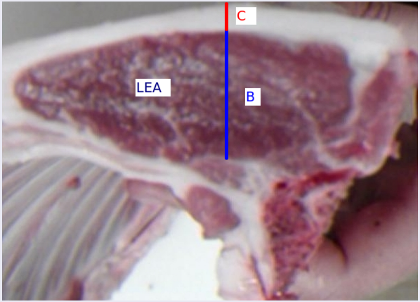
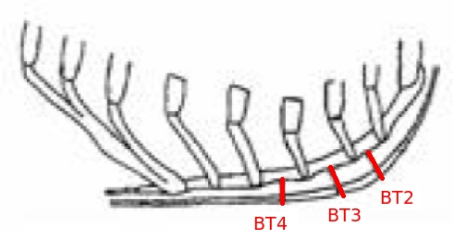


Breast bone tissues thickness

- E2: middle of the 2nd sternebrae



Statistical analysis

Models

- Three multiple equations models were developed to simultaneously predict: LMP, SFP, IFP, BP and KCFP
- All statistical analyses were undertaken using the software R
- Add-on package systemfit
- After estimating the full models by OLS and SUR
  - All explanatory variables that had a parameter with a marginal level of significance (P value) larger than 0.20 were removed.

Statistical analysis

Models fitting quality

- Coefficients of determination of estimation (R_e^2)
- standard error of the estimate (SEE)
- Standard errors (SE) of the estimated parameters

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Models validation

- Leaving-one-out cross-validation procedure
- Predicted residuals sum of squares (PRESS) statistic
- Coefficient of determination of prediction (R_p^2)

Statistical analysis

The base model: C12+E2

$$LMP = \alpha_0 + \alpha_1 HCW + \alpha_2 C12 + \alpha_3 E2 + \varepsilon_1 \quad (1)$$
$$SFP = \beta_0 + \beta_1 HCW + \beta_2 C12 + \beta_3 E2 + \varepsilon_2 \quad (2)$$
$$IFP = \gamma_0 + \gamma_1 HCW + \gamma_2 C12 + \gamma_3 E2 + \varepsilon_3 \quad (3)$$
$$BP = \delta_0 + \delta_1 HCW + \delta_2 C12 + \delta_3 E2 + \varepsilon_4 \quad (4)$$
$$KCFP = \theta_0 + \theta_1 HCW + \theta_2 C12 + \theta_3 E2 + \varepsilon_5 \quad (5)$$

Statistical analysis

The multiple equation model can be written as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_p \end{bmatrix} = \begin{bmatrix} X_1 & 0 & 0 & 0 \\ 0 & X_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & X_p \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_p \end{bmatrix} \tag{6}$$

Statistical analysis

Sub-models

- Sub-model: C12
  with $\alpha_3 = \beta_3 = \gamma_3 = \delta_3 = \theta_3 = 0$
  i.e. without the explanatory variable E2

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  with $\alpha_2 = \beta_2 = \gamma_2 = \delta_2 = \theta_2 = 0$
  i.e. without the explanatory variable C12.

Statistical analysis

OLS estimates of the entire system of equations:

$$\beta^{OLS} = (X'X)^{-1}\,X'y$$

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SUR estimates of the entire system of equations:

$$\beta^{SUR} = \left[X'\Omega^{-1}X\right] \left[X'\Omega^{-1}Y\right]$$

- Ω^{-1} is a weighting matrix based on the covariance matrix of the error terms Σ.
- true error terms ε are unknown
  - replaced by observed residuals obtained from OLS estimates
  - i.e. $\hat{\varepsilon}_i = y_i - X_i\beta_i^{OLS}$
- Thus, a SUR model is an application of the generalized least squares (GLS) approach and the unknown residual covariance matrix is estimated from the data

Descriptive statistics

Table: Correlations among HCW, C12, E2, LMP, SFP, IFP, BP, and KCFP

Variable	C12	E2	LMP	SFP	IFP	BP	KCFP
HCW, kg	0.13	0.52	-0.14	0.20	0.47	-0.55	0.31
C12, mm	1	0.51	-0.36	0.63	0.25	-0.41	0.42
E2, mm		1	-0.61	0.77	0.52	-0.52	0.75
LMP, %			1	-0.84	-0.69	0.14	-0.73
SFP, %				1	0.56	-0.44	0.82
IFP, %					1	-0.63	0.55
BP, %						1	-0.48
KCFP, %							1

Three basic models

Table: Fitting quality for three basic models

Dep. var.	LMP			SFP		
Model	C12	E2	C12+E2	C12	E2	C12+E2
R_e^2	0.140	0.425	0.425	0.415	0.658	0.716
R_p^2	0.051	0.375	0.341	0.351	0.622	0.669
SEE	2.72	2.23	2.25	1.36	1.04	0.961

Three basic models

Table: Fitting quality for three basic models (Cont.)

Dep. var.	IFP			KCFP		
Model	C12	E2	C12+E2	C12	E2	C12+E2
R_e^2	0.252	0.323	0.323	0.238	0.576	0.576
R_p^2	0.164	0.239	0.220	0.164	0.544	0.523
SEE	1.64	1.56	1.58	0.452	0.337	0.342

Three basic models

Table: Fitting quality for three basic models

Dep. var.		BP	
Model	C12	E2	C12+E2
R_e^2	0.411	0.373	0.425
R_p^2	0.346	0.303	0.338
SEE	1.401	1.45	1.404

Residuals correlations

Table: Residuals correlations for model E2 estimated by ordinary least squares method (OLS)

	LMP	SFP	IFP	KCFP	BP
LMP	1	-0.709	-0.670	-0.505	-0.189
SFP		1	0.445	0.569	-0.242
IFP			1	0.337	-0.446
KCFP				1	-0.229
BP					1

Model E2a

Table: Fitting quality of model E2a

Dep. var.	LMP		SFP		IFP	
Est. method	OLS	SUR	OLS	SUR	OLS	SUR
R_e^2	0.425	0.413	0.657	0.649	0.323	0.317
R_p^2	0.375	0.382	0.636	0.631	0.239	0.242
SEE	2.23	2.25	1.03	1.04	1.56	1.56

Model E2a

Table: Fitting quality of model E2a

Dep. var.	KCFP		BP	
Est. method	OLS	SUR	OLS	SUR
R_e^2	0.533	0.533	0.373	0.371
R_p^2	0.534	0.534	0.303	0.302
SEE	0.344	0.344	1.445	1.448

Conclusions

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Conclusions

1. Novel approach to simultaneously predict carcass components using the SUR technique
2. The SUR estimator provides the lowest standard errors of the estimated parameters
3. SUR is a robust methodology for predicting the carcass composition
4. Results are relevant for implementing objective carcass classification systems to simultaneously predict carcass components
5. Our findings can have a positive effect on the meat industry, since the methodology can improve decision support systems by using all carcass tissues to determine the price as well as the optimal processing (e.g., refrigeration conditions) of the carcasses

THE END!

Thank You for Your Attention

Obrigado pela Atenção

Hvala na Pozornosti