

## **Recursive binomial model to analyze piglet survival in a diallel cross between iberian pigs**

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# INTRODUCTION (I)

- Pig mortality is a categorical trait with great relevance in pig production
- Several models has been proposed (Varona and Sorensen, 2010; Genetics 184: 277-284)
  - Poisson
  - Binomial
  - Negative Binomial
  - Zero Inflated Poisson
  - Zero Inflated Binomial
  - Zero Inflated Negative Binomial.
- The model with best adjustment (logCPO) was the binomial model.

# INTRODUCTION (II)

- Pig mortality is related with litter size.
- To model genetic and residual relationships between continuous and binomial traits is not an easy task.
- One alternative is the use of structural models (Gianola y Sorensen, 2004; Genetics 167: 1407-1424).
- In a previous study, a non-linear recursive model was proposed (Varona y Sorensen, 2014; Genetics 196: 643-651).
- Recursive parameters can be modeled globally or related with any systematic effects (such as population or cross type).

## A

## OBJECTIVE

To estimate the direct, maternal and heterosis effects for pig mortality in a diallel cross between three varieties of Iberian pig: Retinto (RR), Torbiscal (TT) and Entrepelado (EE) and its relationships with litter size using non-linear recursive models

## B

## MATERIAL

- EE: 2843 records from 707 sows
- ER: 2336 from 527
- ET: 942 from 177
- RE: 806 from 196
- RR: 4472 from 874
- RT: 2450 from 488
- TE: 193 from 36
- TR: 1993 from 359
- TT: 2158 from 452
- TOTAL: 18193 from 3816



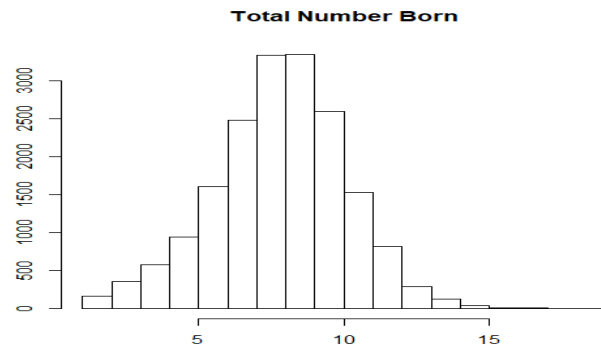
ENTREPELADO (EE)



RETINTO (RR)



TORBISCAL (TT)



$$f(\mathbf{y}|\mathbf{t}, \boldsymbol{\phi}) = \prod_{i=1}^N \binom{t_i}{y_i} \phi_i^{y_i} (1 - \phi_i)^{t_i - y_i}$$

$$\text{logit } \boldsymbol{\phi} = \mathbf{X}\mathbf{b}_l + \mathbf{Z}\mathbf{u}_l + \mathbf{Z}\mathbf{p}_l + \lambda_1 \mathbf{t} + \lambda_2 \mathbf{t}^2$$

$$\mathbf{t} = \mathbf{X}\mathbf{b}_t + \mathbf{Z}\mathbf{u}_t + \mathbf{Z}\mathbf{p}_t + \mathbf{e}$$

$$\begin{pmatrix} \mathbf{u}_l \\ \mathbf{u}_t \end{pmatrix} \sim N(\mathbf{0}, \mathbf{A} \otimes \mathbf{G}) \quad \begin{pmatrix} \mathbf{p}_l \\ \mathbf{p}_t \end{pmatrix} \sim N(\mathbf{0}, \mathbf{I} \otimes \mathbf{P})$$

$$f(\mathbf{y}|\mathbf{t}, \boldsymbol{\phi}) = \prod_{i=1}^N \binom{t_i}{y_i} \phi_i^{y_i} (1 - \phi_i)^{t_i - y_i}$$

$$\text{logit } \phi = \mathbf{X}\mathbf{b}_l + \mathbf{Z}\mathbf{u}_l + \mathbf{Z}\mathbf{p}_l + \sum_{k=1}^{N_{pop}} \lambda_{1k} t_k + \lambda_{2k} t_k^2$$

$$t_k = \begin{cases} t & \text{if } k \text{ population} \\ \mathbf{0} & \text{if not } k \text{ population} \end{cases}$$

$$\mathbf{t} = \mathbf{X}\mathbf{b}_t + \mathbf{Z}\mathbf{u}_t + \mathbf{Z}\mathbf{p}_t + \mathbf{e}$$

$$\begin{pmatrix} \mathbf{u}_l \\ \mathbf{u}_t \end{pmatrix} \sim N(\mathbf{0}, \mathbf{A} \otimes \mathbf{G}) \quad \begin{pmatrix} \mathbf{p}_l \\ \mathbf{p}_t \end{pmatrix} \sim N(\mathbf{0}, \mathbf{I} \otimes \mathbf{P})$$

# D RESULTS: VARIANCE COMPONENTS

## MODEL 1

	Val	Vat	ra	Vpl	Vpt	rp	Ve	LogCPO
Mean	0.251	0.533	-0.132	0.798	0.374	0.124	4.018	-38074.37
SD	0.061	0.070	0.136	0.061	0.051	0.079	0.048	

## MODEL 2

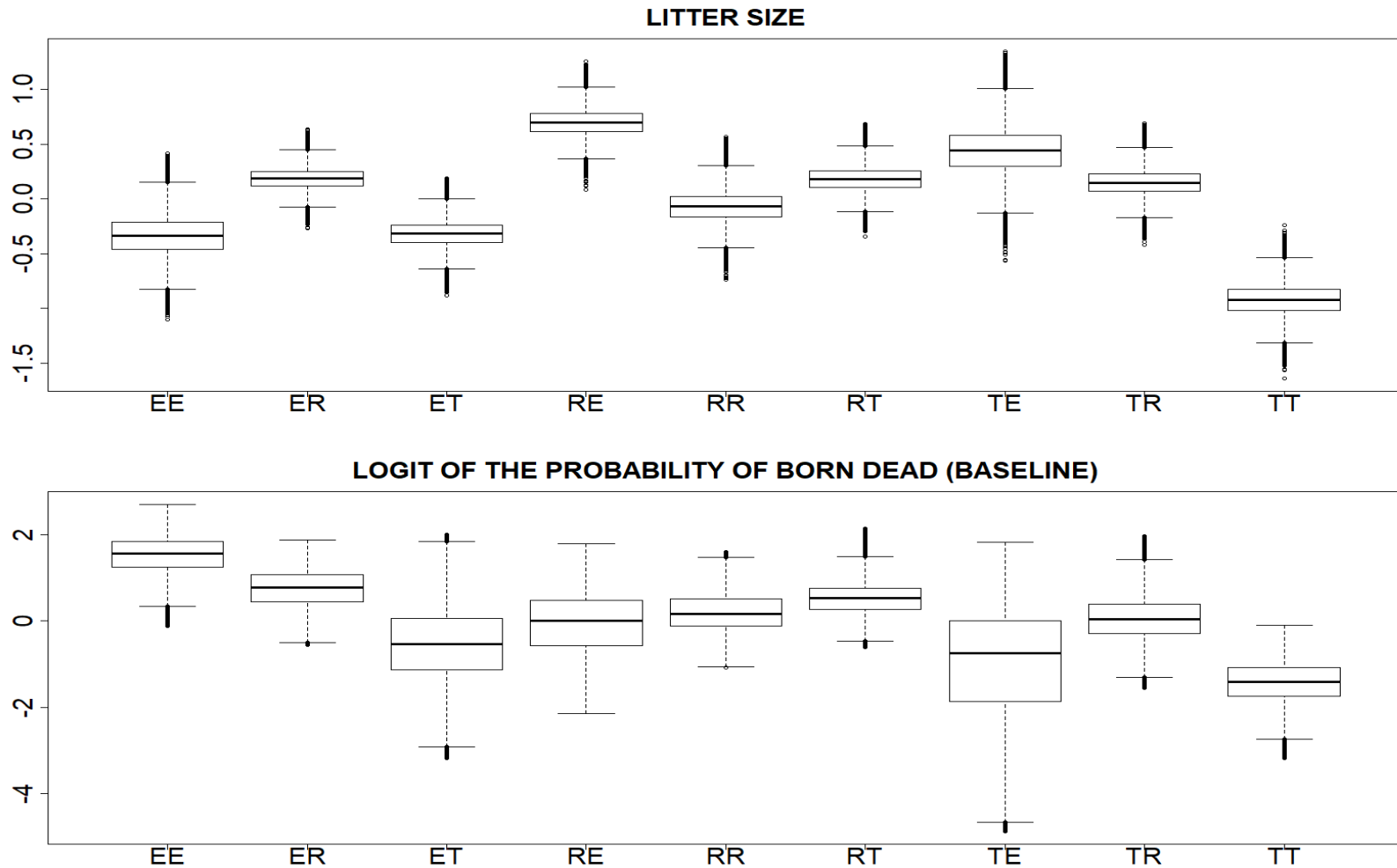
	Val	Vat	ra	Vpl	Vpt	rp	Ve	LogCPO
Mean	0.066	0.542	0.063	0.921	0.369	0.112	4.018	-37817.12
SD	0.040	0.072	0.214	0.062	0.053	0.074	0.048	

Gibbs Sampler 525.000 iterations (25.000 burn in)



D

## RESULTS: POPULATION EFFECTS



## D

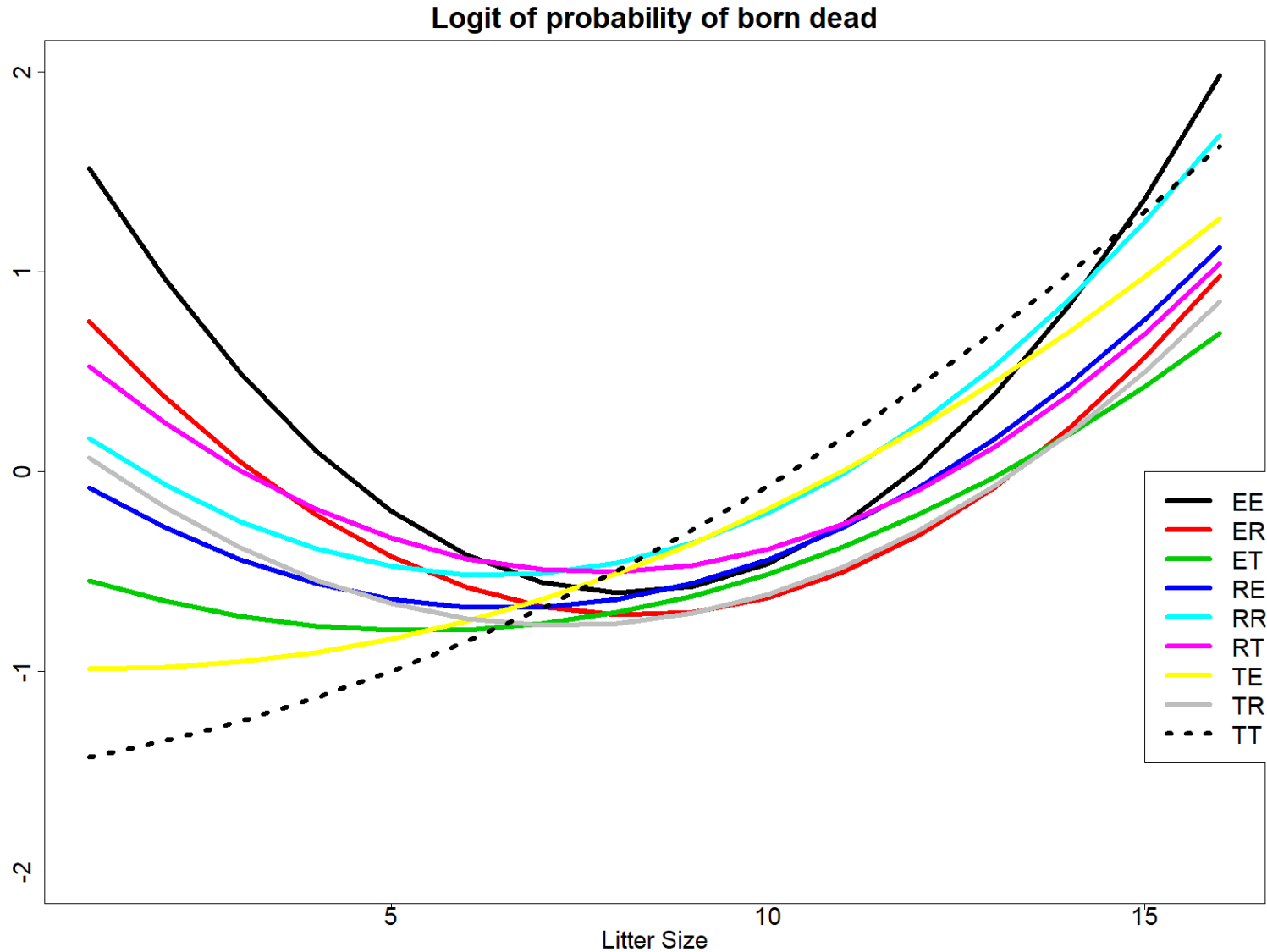
## RESULTS: DICKERSON'S MODEL

	LE	LR	LT	ME	MR	MT	HER	HET	HER
Litter Size									
Mean	-0.31	0.55	-0.24	0.42	-0.18	-0.24	0.64	0.69	0.66
SD	0.20	0.15	0.16	0.10	0.06	0.09	0.10	0.15	0.09
Logit of the probability of born dead (baseline)									
Mean	1.85	-0.01	-1.83	-0.41	0.10	0.31	-0.51	-0.84	0.92
SD	0.97	0.50	0.90	0.86	0.36	0.74	0.59	0.82	0.47

Red: Posterior probability over (or above) zero greater than 0.95

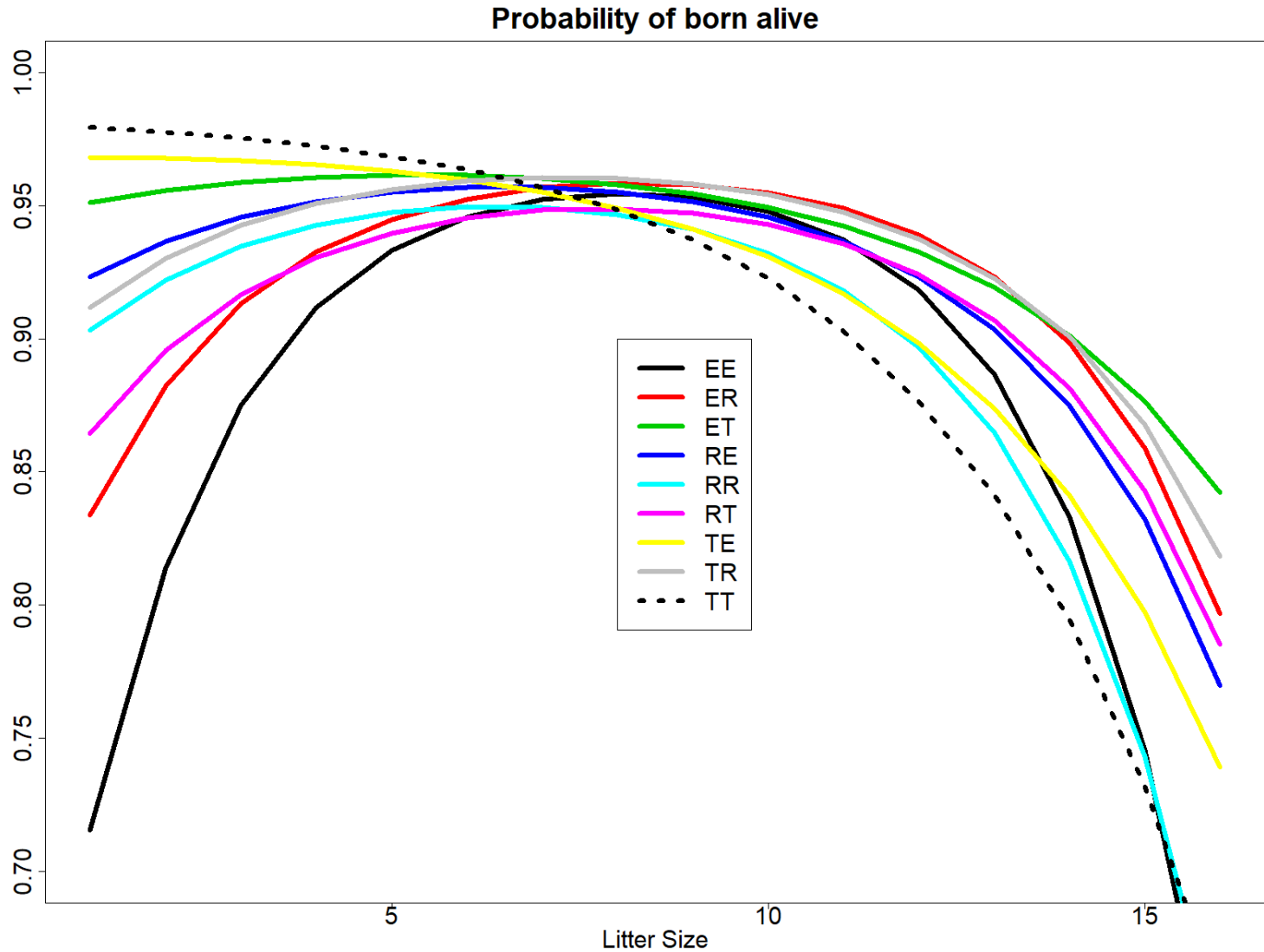
D

## RESULTS: POPULATION EFFECTS



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## RESULTS: POPULATION EFFECTS



## D

## RESULTS: DICKERSON'S MODEL

Litter size: 5

	LE	LR	LT	ME	MR	MT	HER	HET	HRT
Mean	0.20	0.15	-0.35	-0.02	-0.07	0.09	-0.17	-0.14	0.09
SD	0.27	0.15	0.25	0.25	0.10	0.21	0.17	0.28	0.14

Litter size: 9

	LE	LR	LT	ME	MR	MT	HER	HET	HRT
Mean	-0.39	0.18	0.21	0.17	-0.13	0.03	-0.20	-0.08	-0.36
SD	0.14	0.10	0.13	0.11	0.06	0.10	0.12	0.17	0.11

Litter size: 13

	LE	LR	LT	ME	MR	MT	HER	HET	HRT
Mean	-0.40	0.29	0.11	0.25	-0.14	-0.10	-0.52	-0.47	-0.64
SD	0.19	0.13	0.19	0.14	0.09	0.14	0.15	0.24	0.15

# CONCLUSIONS

- The population of Retinto (R) has the best direct effect for litter size, while Entrepelado (E) has the greatest maternal effect.
- There are large effects of heterosis for litter size.
- The crossbreeding parameters for swine mortality varied with the size of the litter.
- There is no heterosis effect for porcine mortality with low prolificacy, and it seems to appear when the litter size increases.
- Non-linear recursive models are a plausible approximation for the nonlinear relationship between traits.

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