

# A Bayesian Model for the Validation of Magnetic Resonance Imaging (MRI) as a Surrogate Endpoint for a Clinical Endpoint

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# Research team

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## Academia

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## Industry

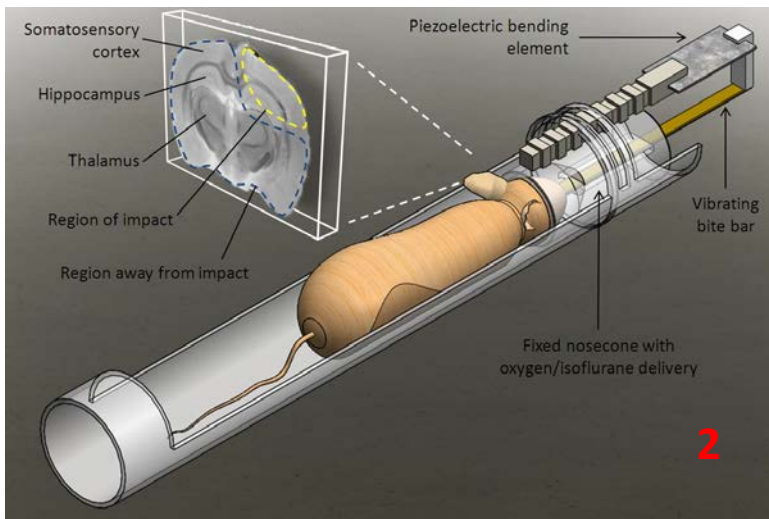
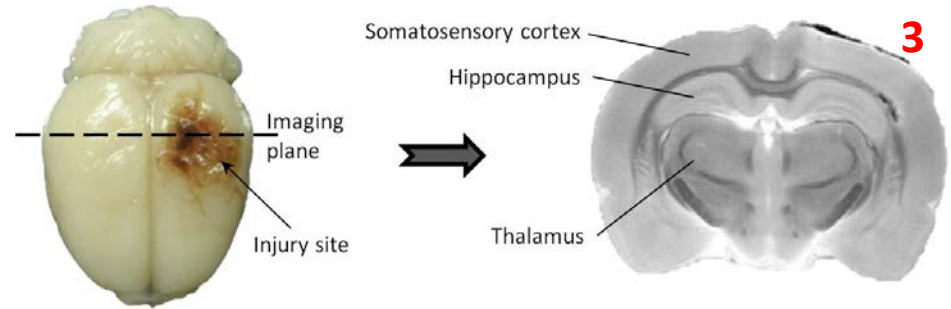
- Janssen
  - Luc Bijmens
  - Darrel Pemberton
  - Marc Schmidt
  - Others
- Icometrix
- Histogenix
- Open Analytics
- The MRI Consortium

# Introduction

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- Alzheimer disease: age-dependent, irreversible.
- Non-invasive screening tools desirable for early detection and management.
- Identification and validation of potential bio-markers crucial- a lot of ongoing research.
- *Evaluate the use of Magnetic Resonance Imaging (MRI) as a surrogate for disease progression*

# MR Image acquisition



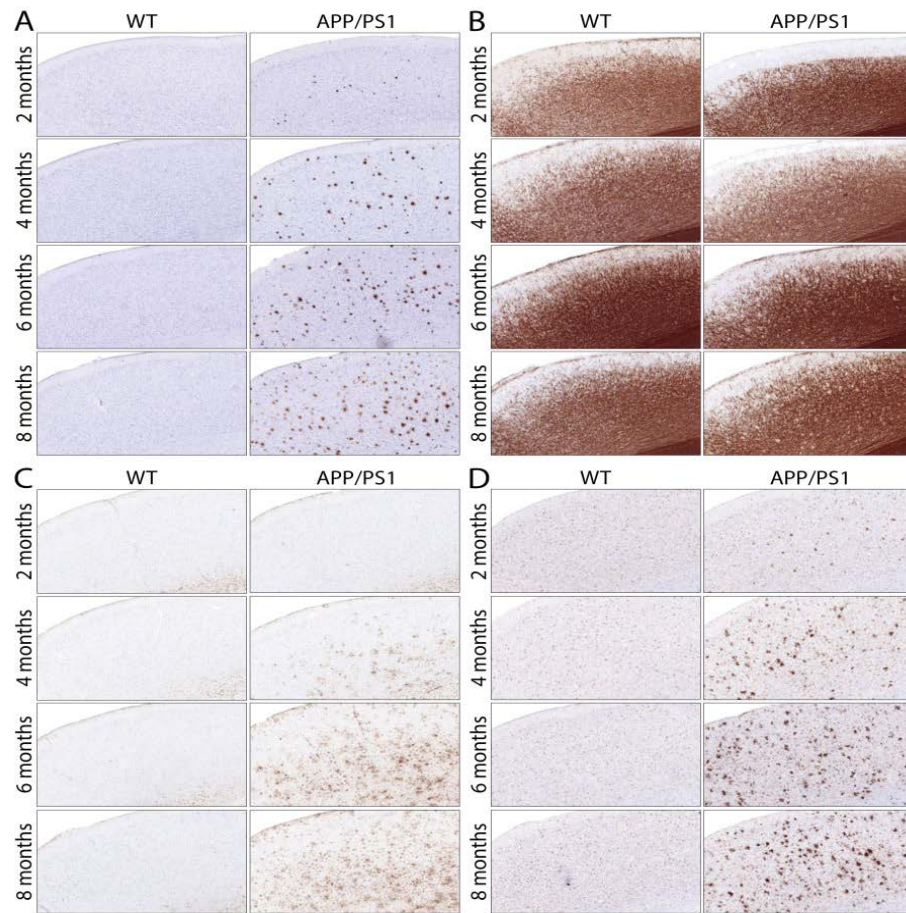
Numeric values for different parameters

- Diffusion kurtosis imaging
  - Mean Kurtosis (MK)
  - Axial Kurtosis (AK)
  - Radial Kurtosis (RK)
- Diffusion tensor imaging
  - Mean Diffusivity (MD)
  - Axial Diffusivity (AD)
  - Radial Diffusivity (RD)
  - Fractional Anisotropy (FA)

Note: MRI can be acquired longitudinally

Images downloaded from: [TREM](#), [MRSolutions](#)

# Histology Staining: Cortex Motor



A: 4G8  
B: MBP  
C: GFAP  
D: IBA1

- Different histology stains enable detection of different structures
- Plaque deposits are quantified
  - % stained area
  - Mean intensity
- Numeric values for statistical analysis
  - MBP staining
  - GFAP staining
  - Iba1 staining
  - 4G8 staining
- Note: **Only one set of histology measurements per animal**

# Data

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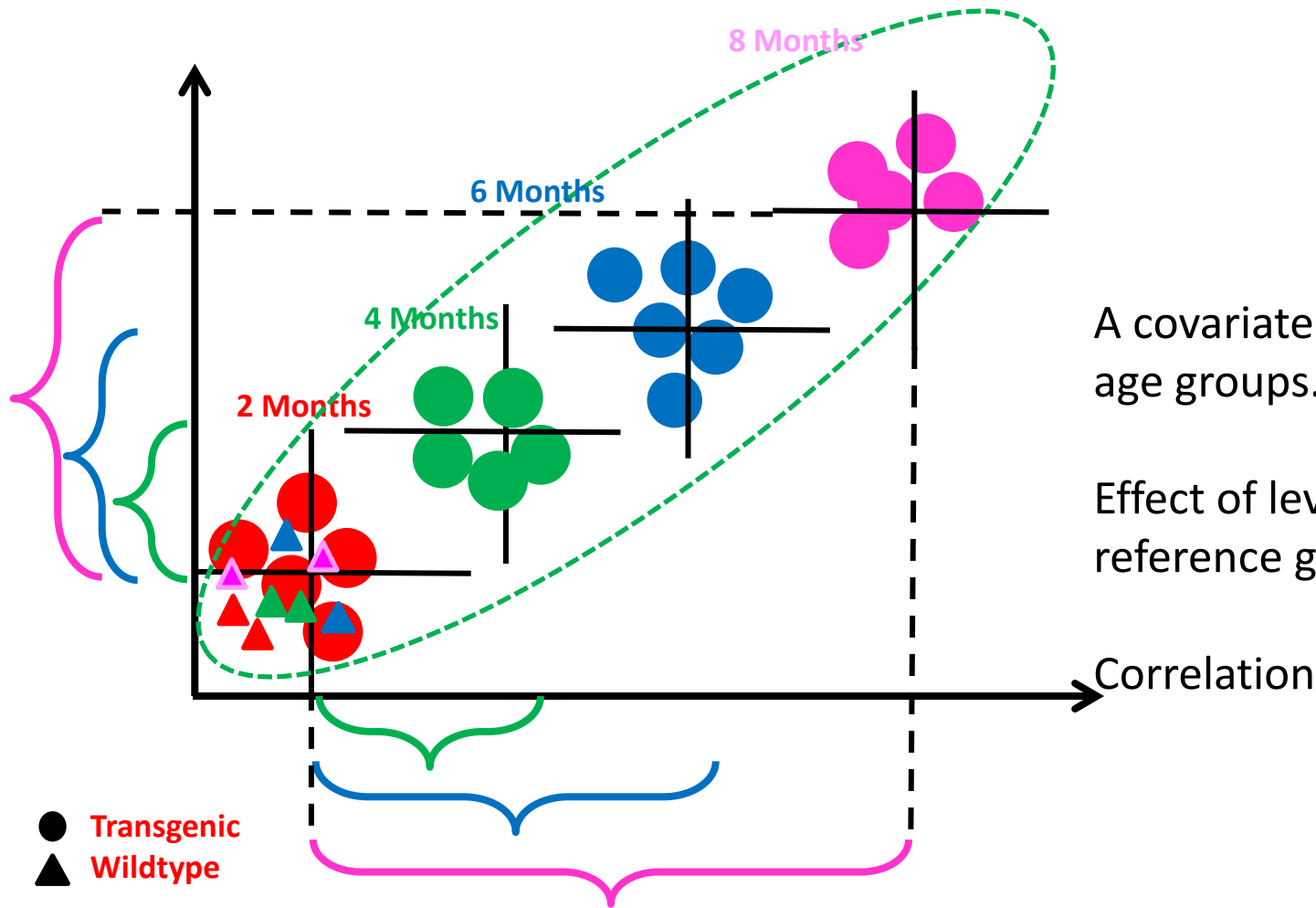
- Histology can only be acquired once per animal.
- Cross-sectional studies at 2, 4, 6 and 10 months with MRI and histology available.
- Longitudinal MRI study with histology at 8 months
- Resulting into 4 cross-sectional (multivariate) datasets
- 23 brain ROI, 7 MRI parameters, 4 histology parameters
- $23 \times 7 \times 4 = 664$  models

# Evaluation of MRI as biomarker for histology

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- Methodology: surrogate endpoints in clinical trials.
- Histology: “true” endpoint.
- MRI: “surrogate” endpoint.
  
- Can we use MRI as a surrogate to histology ?
- Can we replace histology with MRI ?

# Illustration: Disease Effects



A covariate with 4 levels = 4 age groups.

Effect of level  $j$  compare to the reference group.



# Two-stage Surrogacy Model

Given a 'True' endpoint T and a surrogate endpoint S,

The two-stage model for surrogacy can generally be denoted as:

$$\begin{pmatrix} T_{ij} \\ S_{ij} \end{pmatrix} \sim N \left( \begin{bmatrix} \mu_{T_j} + \alpha_j Z_i \\ \mu_{S_j} + \beta_j Z_i \end{bmatrix}, \Sigma_k \right) \quad \longrightarrow \quad \text{Component for deriving individual-level surrogacy}$$
$$\begin{pmatrix} \alpha_j \\ \beta_j \end{pmatrix} \sim N \left( \begin{bmatrix} \bar{\alpha} \\ \bar{\beta} \end{bmatrix}, D \right) \quad \longrightarrow \quad \text{Component for deriving trial-level surrogacy}$$

# Joint Model for MRI and Histology at ROI

For a given region in the brain, MRI parameter and histology stain

$$T_{ij} = \mu_{T_j} + \alpha_j Z_i + \varepsilon_{T_{ij}}$$

$$S_{ij} = \mu_{S_j} + \beta_j Z_i + \varepsilon_{S_{ij}}$$

$$\begin{pmatrix} \varepsilon_{T_{ij}} \\ \varepsilon_{S_{ij}} \end{pmatrix} \sim N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Sigma_k \right), k = 1, 2$$

$$\text{Transgenic} : \Sigma_1 = \begin{pmatrix} \sigma_{App,hist}^2 & \sigma_{App,hist:mri} \\ \sigma_{App,hist:mri} & \sigma_{App,mri}^2 \end{pmatrix}$$

$$\text{Wildtype} : \Sigma_2 = \begin{pmatrix} \sigma_{Wt,hist}^2 & \sigma_{Wt,hist:mri} \\ \sigma_{Wt,hist:mri} & \sigma_{Wt,mri}^2 \end{pmatrix}$$

# Two Measures of Surrogacy

## 1: Individual-level surrogacy

$$\Sigma_k \Rightarrow \rho(MRI, Hist.)$$

$$\text{Transgenic} : \rho_1 = \frac{\sigma_{App,hist:mri}}{\sqrt{\sigma_{App,mri}^2 \cdot \sigma_{App,hist}^2}}$$

$$\text{Wildtype} : \rho_2 = \frac{\sigma_{Wt,hist:mri}}{\sqrt{\sigma_{Wt,mri}^2 \cdot \sigma_{Wt,hist}^2}}$$

## 2: Disease- level surrogacy

- Correlation between the disease effects

$$D \Rightarrow \rho(\alpha_j, \beta_j)$$

$$\rho_D = \frac{\sigma_{\alpha,\beta}}{\sqrt{\sigma_{\alpha}^2 \cdot \sigma_{\beta}^2}}$$

- Predicting effects in histology by the effects in MRI

# Bayesian Prior Specification

$$\mu_{S_j} \sim N(0.0, \tau_{SS}),$$

$$\mu_{T_j} \sim N(0.0, \tau_{TT}),$$

$$\tau_{SS} \sim \text{Gamma}(0.001, 0.001),$$

$$\tau_{TT} \sim \text{Gamma}(0.001, 0.001),$$

$$\Sigma_1^{-1} \sim \text{Wishart}(R_W, \phi),$$

$$\Sigma_2^{-1} \sim \text{Wishart}(R_A, \phi),$$

$$\begin{pmatrix} \alpha_j \\ \beta_j \end{pmatrix} \sim N \left( \begin{pmatrix} \bar{\mu}_S \\ \bar{\mu}_T \end{pmatrix}, D_{22} \right),$$

$$D_{22}^{-1} \sim \text{Wishart}(R_{D_{22}}, \phi),$$

$$\bar{\mu}_S \sim N(0.0, 1.0E - 6),$$

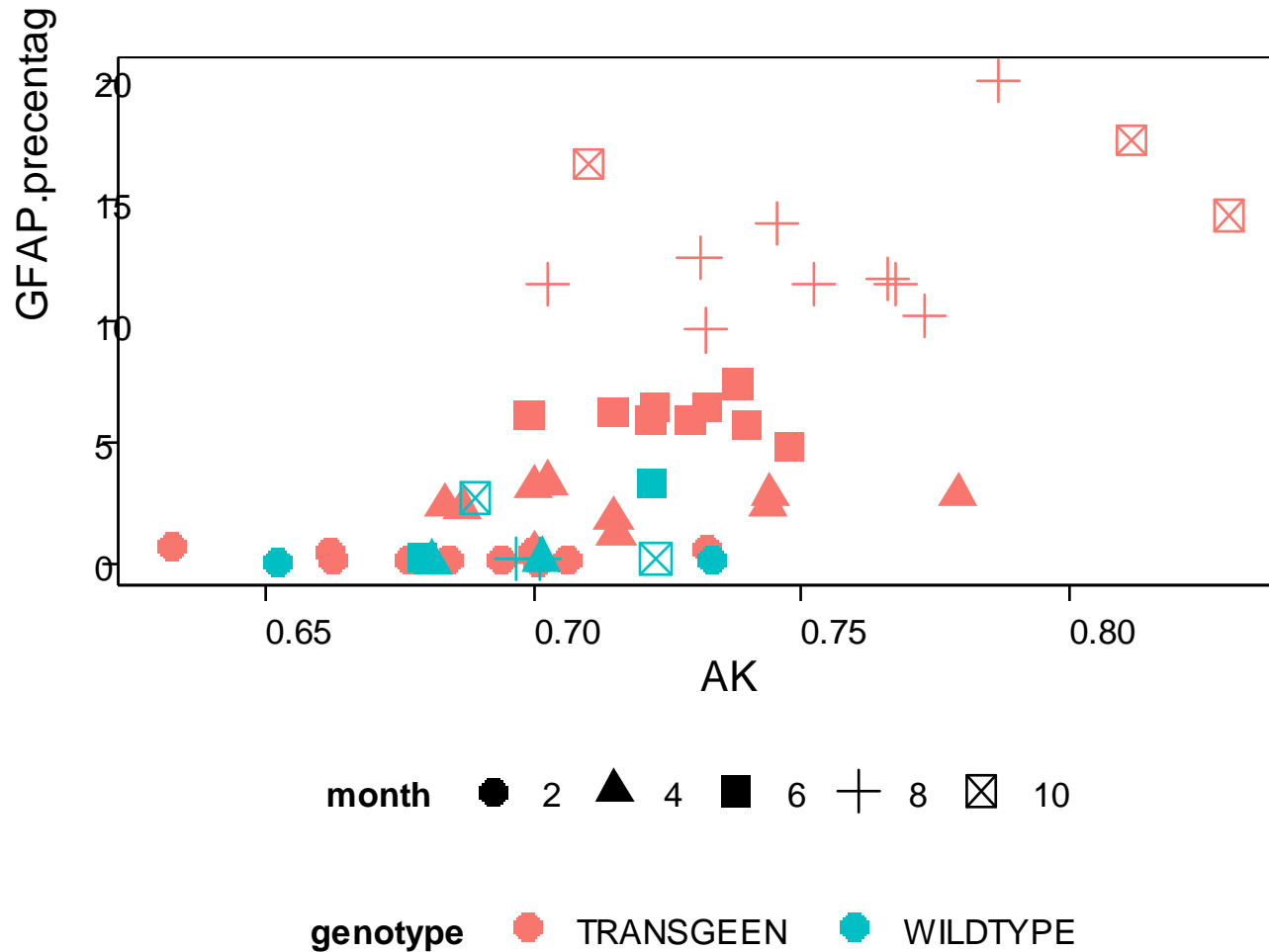
$$\bar{\mu}_T \sim N(0.0, 1.0E - 6).$$



# Example 1

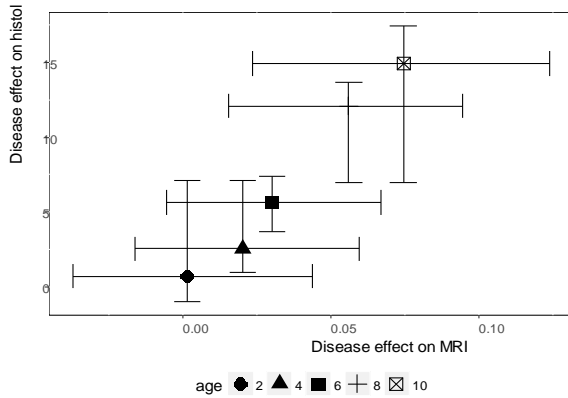
Cortex Motor: MRI-AK with GFAP Staining

# Cortex Motor: Observed Data (MRI-AK with GFAP)

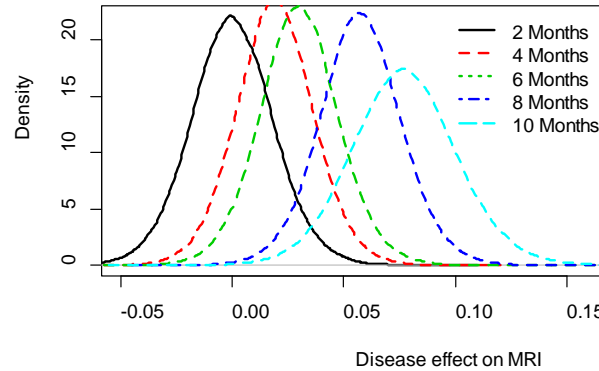


# Results: Cortex Motor (MRI-AK with GFAP)

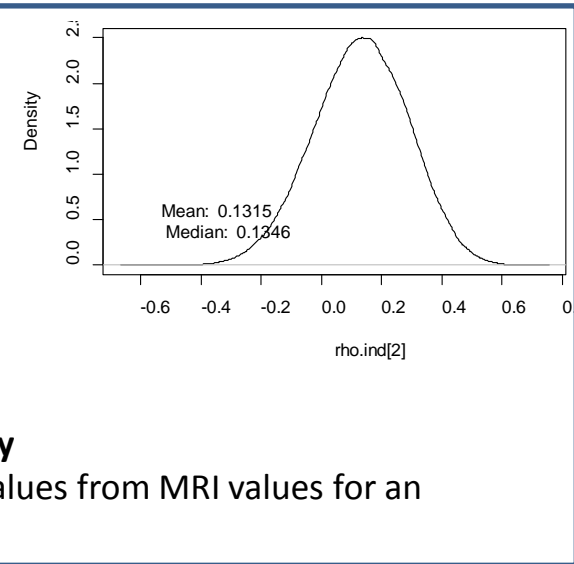
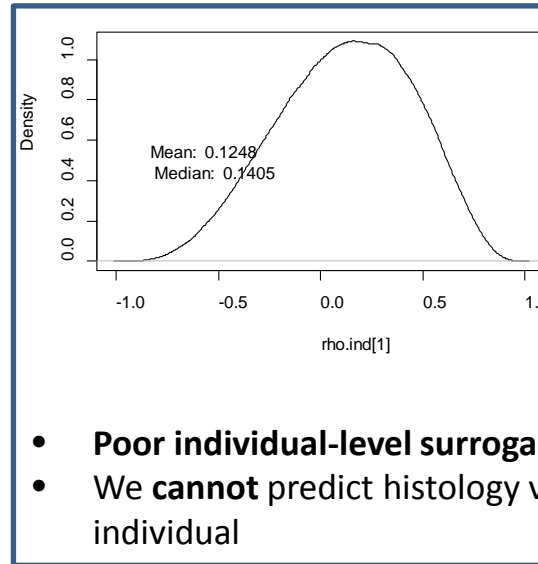
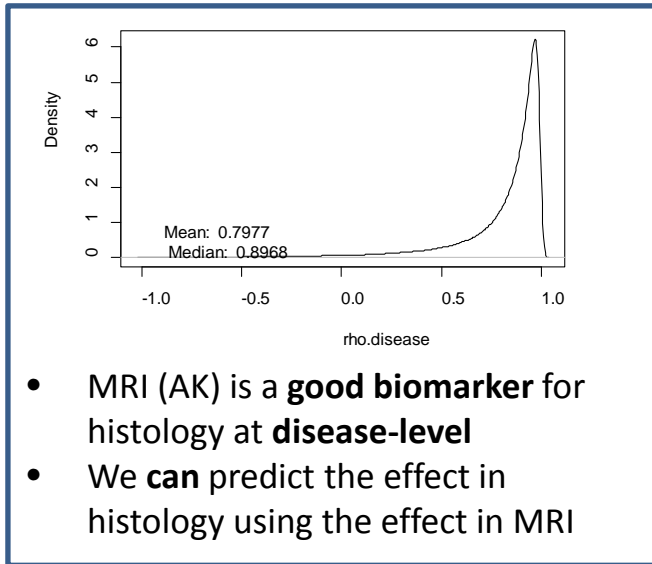
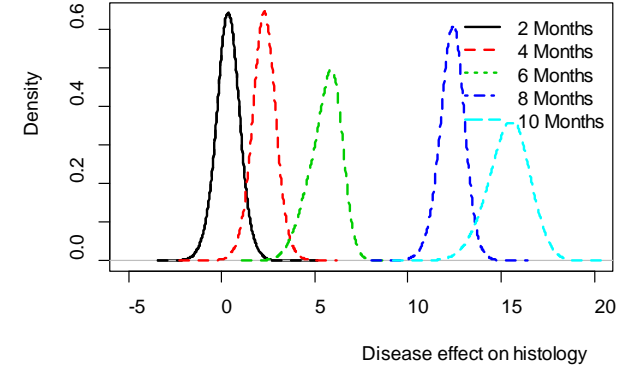
Posterior means with error bars



Disease effects on MRI



Disease effect on histology



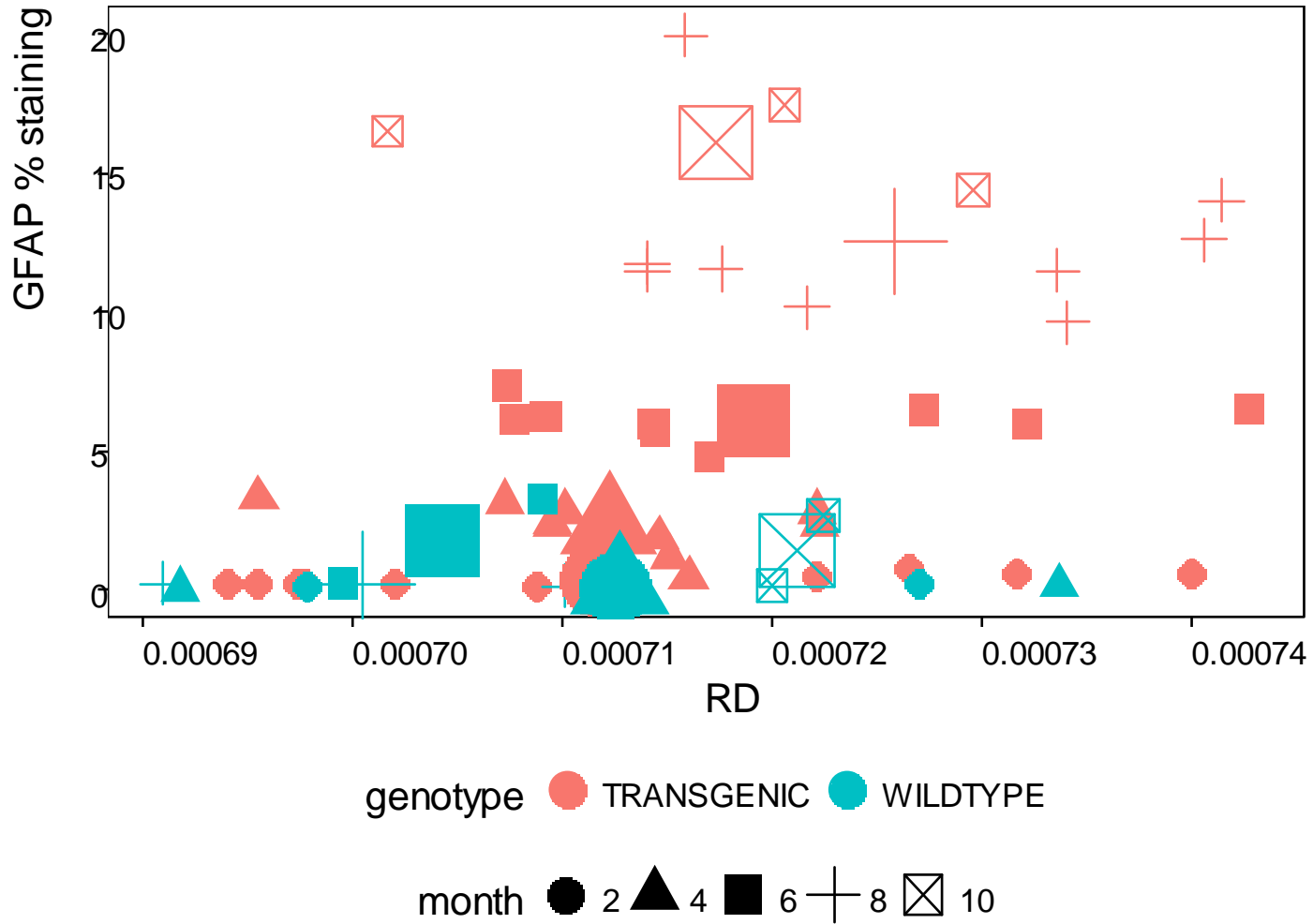


## Example 2

Cortex Motor: MRI-RD with GFAP Staining

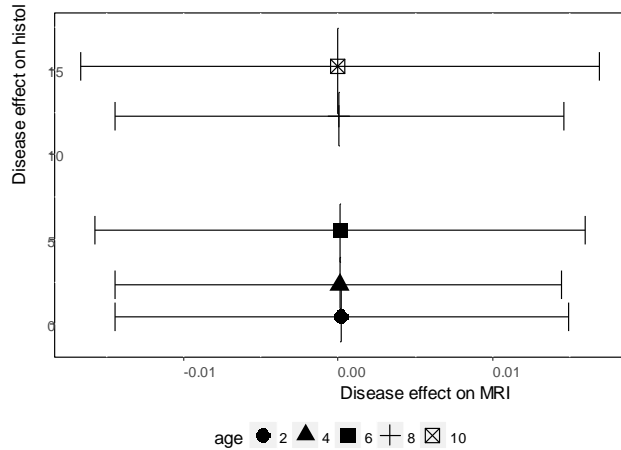


# Cortex Motor: Observed Data (MRI-RD with GFAP)

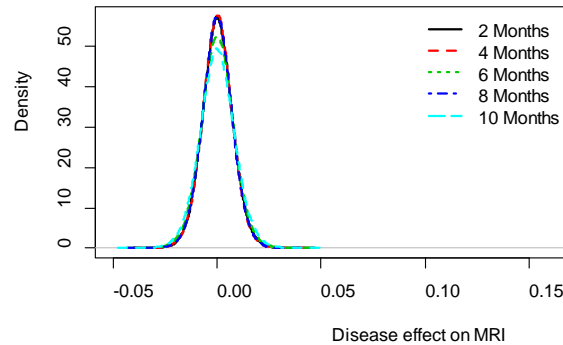


# Results: Cortex Motor (MRI-RD with GFAP)

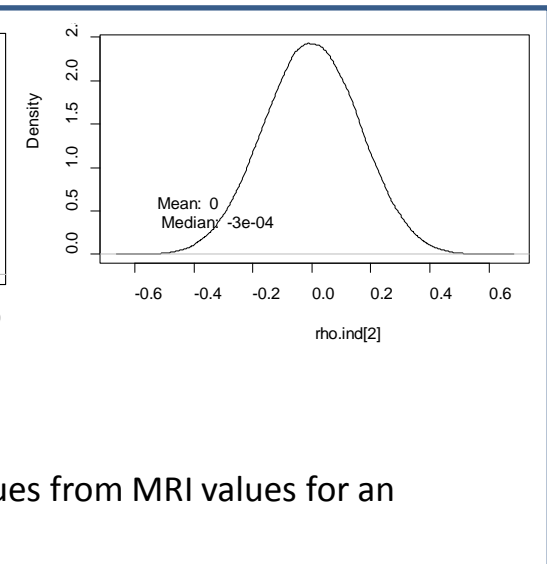
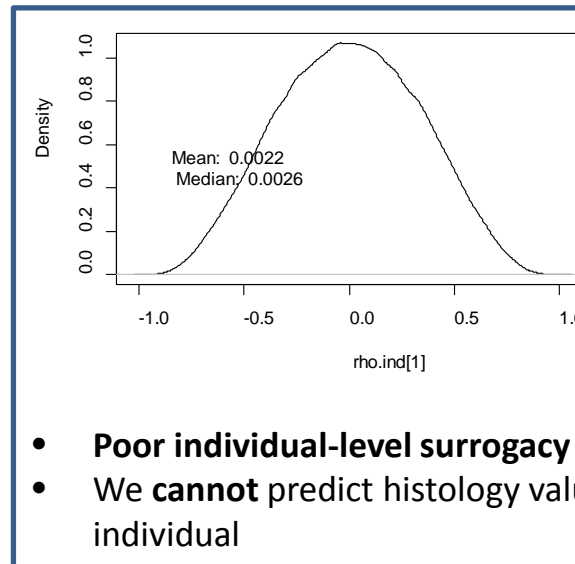
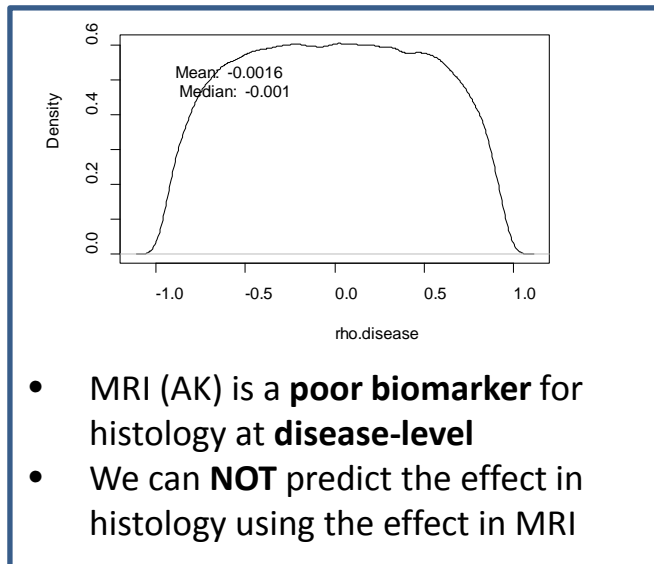
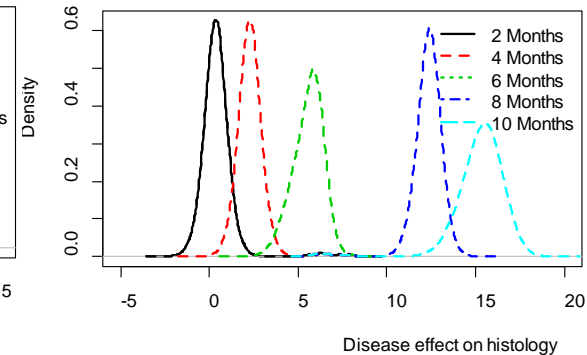
Posterior means with error bars



Disease effects on MRI



Disease effect on histology



# Conclusion

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- MRI has potential to be a biomarker at disease level
- Surrogacy depends on MRI parameters, histology stain and brain region
- Assess model improvement at resolution higher than the ROI (unit level analysis)
- Evaluation of multivariate markers jointly?