

**Feb 14**

Expanding on  
Poisson regressions

1. Administrative
2. Interpreting coefficients from Poisson regressions
3. Over-dispersed Poisson regressions
4. Zero-inflated Poisson regressions
5. Over-dispersion and zero-inflation in R

# Interpreting coefficients

Model from last time

$H_i \sim \text{Pois}(\lambda_i)$		
$\log(\lambda_i) = \alpha + \beta_M M_i + \beta_G G_i$		
	<b><math>\alpha</math></b>	1.32
	<b><math>\beta_M</math></b>	3.05
	<b><math>\beta_G</math></b>	0.87
$\alpha \sim \text{Norm}(3, 1)$		
$\beta_M \sim \text{Norm}(0, 0.5)$		
$\beta_G \sim \text{Norm}(0, 0.3)$		

## $\alpha$ (baseline)

A student who is not a boy ( $M_i=0$ ) and is in grade 10 ( $G_i=0$ ) is predicted to play about 1.32 hours of games per week.

## $\beta_M$ (gender)

Boys ( $M_i=1$ ) are expected to spend about 3.05 times more time than non-boys ( $M_i=0$ ) playing games.

## $\beta_G$ (grade)

A one-year increase in grade is associated with playing 0.87 times as much. This is a decrease of 13% each year.

# Over-dispersion

$$H_i \sim \text{Pois}(\lambda_i)$$

$$\log(\lambda_i) = \alpha + \beta M_i$$

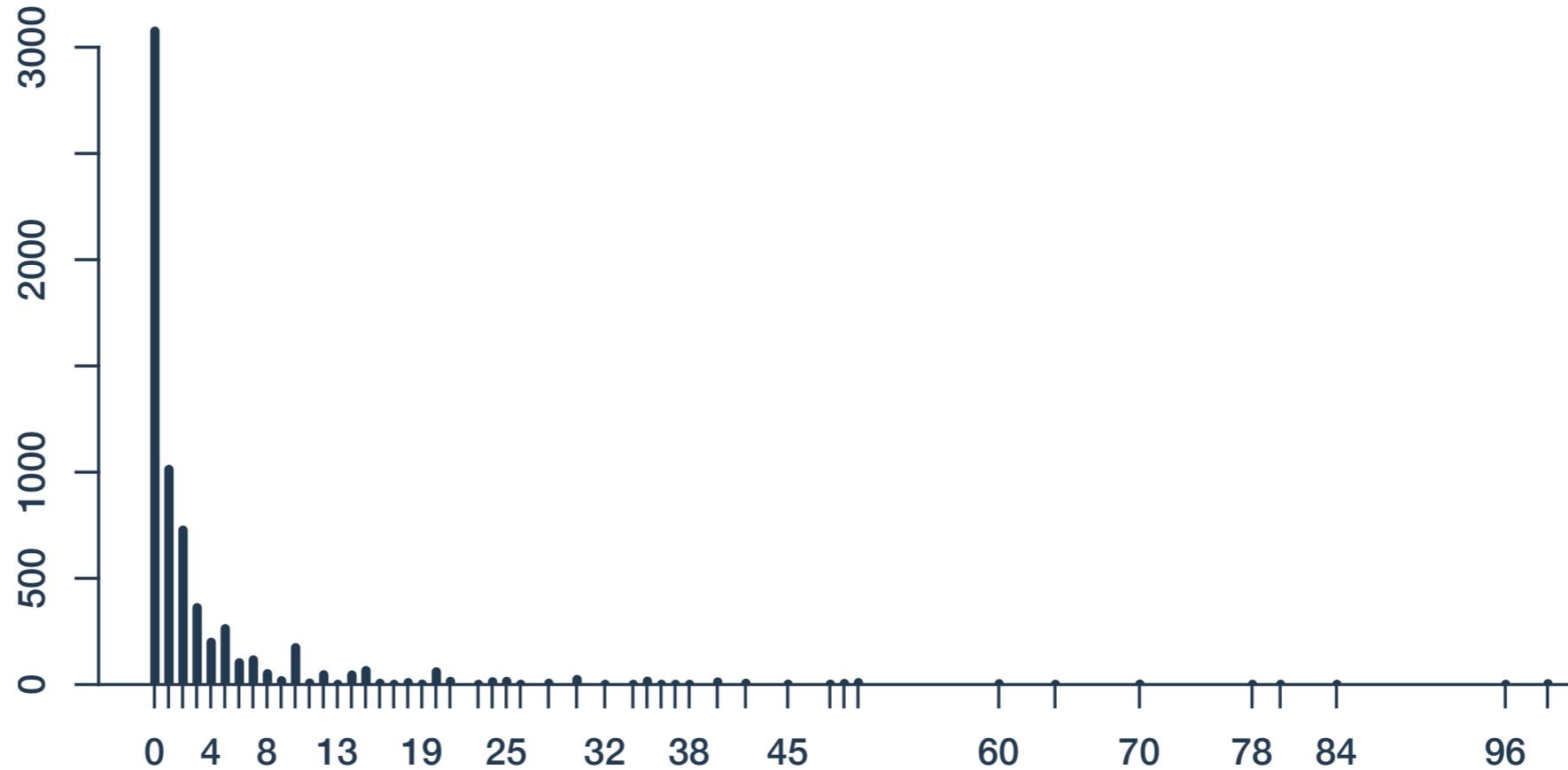
$$\alpha \sim \text{Norm}(3, 0.5)$$

$$\beta \sim \text{Norm}(0, 0.3)$$

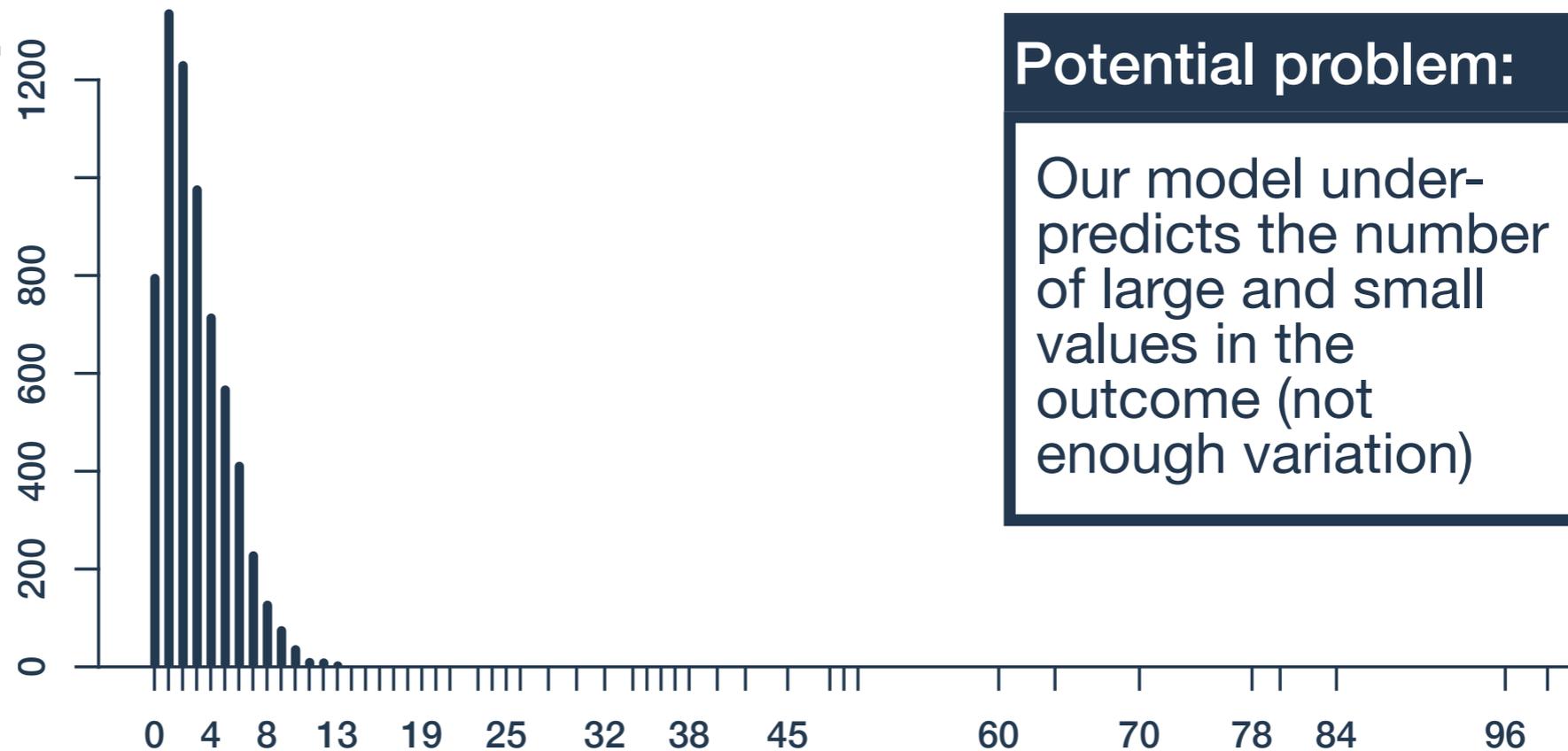
	<i>Mean</i>	<i>exp(Mean)</i>
<b><math>\alpha</math></b>	0.27	1.32
<b><math>\beta</math></b>	1.11	3.05

# Over-dispersion

**Actual distribution**



**Posterior predicted distribution (Poisson regression)**



## Potential problem:

Our model under-predicts the number of large and small values in the outcome (not enough variation)

# Over-dispersion

## Poisson regression

$$H_i \sim \text{Pois}(\lambda_i)$$

$$\log(\lambda_i) = a + \beta M_i$$

$$a \sim \text{Norm}(3, 0.5)$$

$$\beta \sim \text{Norm}(0, 0.3)$$

## Gamma-Poisson regression

$$H_i \sim \text{Pois}(\lambda_i)$$

$$\lambda_i \sim \text{Gamma}(\mu_i, \theta)$$

$$\log(\mu_i) = a + \beta M_i$$

$$a \sim \text{Norm}(3, 0.5)$$

$$\beta \sim \text{Norm}(0, 0.3)$$

$$\theta \sim \text{Unif}(0, 10)$$

Extra “dispersion”  
from gamma

Two students who  
look identical based  
on covariates can  
have different  
Poisson rates  $\lambda_i$ .

One more prior

A.K.A.

Negative-binomial regression

Over-dispersed Poisson regression

# Over-dispersion

## Gamma-Poisson regression

$$H_i \sim \text{Pois}(\lambda_i)$$

$$\lambda_i \sim \text{Gamma}(\mu_i, \theta)$$

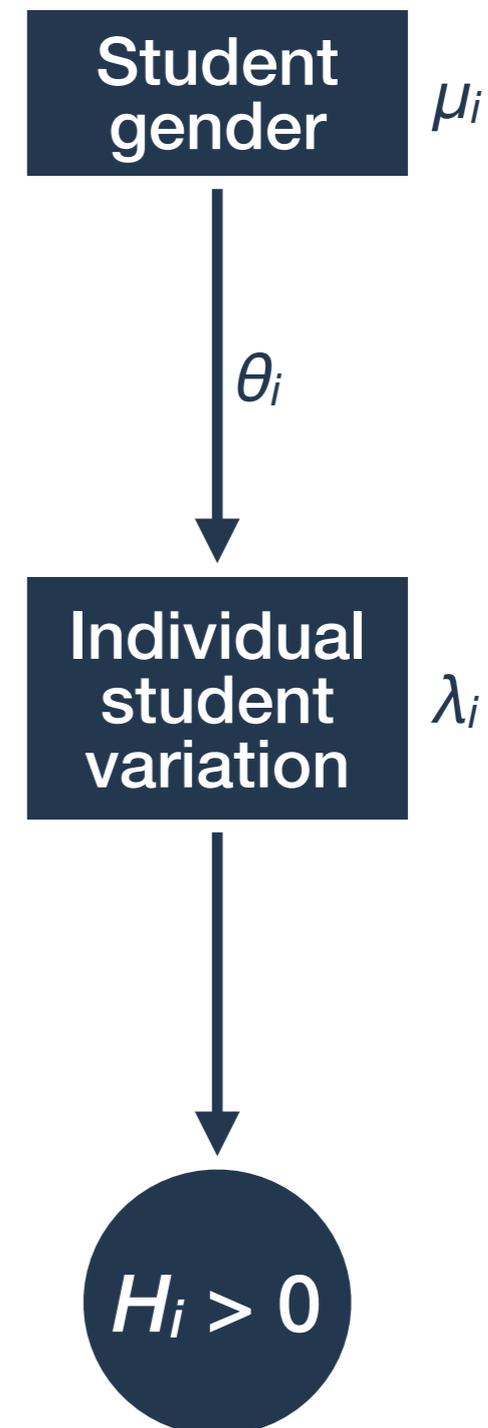
$$\log(\mu_i) = a + \beta M_i$$

$$a \sim \text{Norm}(3, 0.5)$$

$$\beta \sim \text{Norm}(0, 0.3)$$

$$\theta \sim \text{Unif}(0, 10)$$

## Data story:



# Over-dispersion

$$H_i \sim \text{GammaPois}(\lambda_i, \theta)$$

$$\log(\lambda_i) = \alpha + \beta M_i$$

$$\alpha \sim \text{Norm}(3, 0.5)$$

$$\beta \sim \text{Norm}(0, 0.3)$$

$$\theta \sim \text{Unif}(0, 10)$$

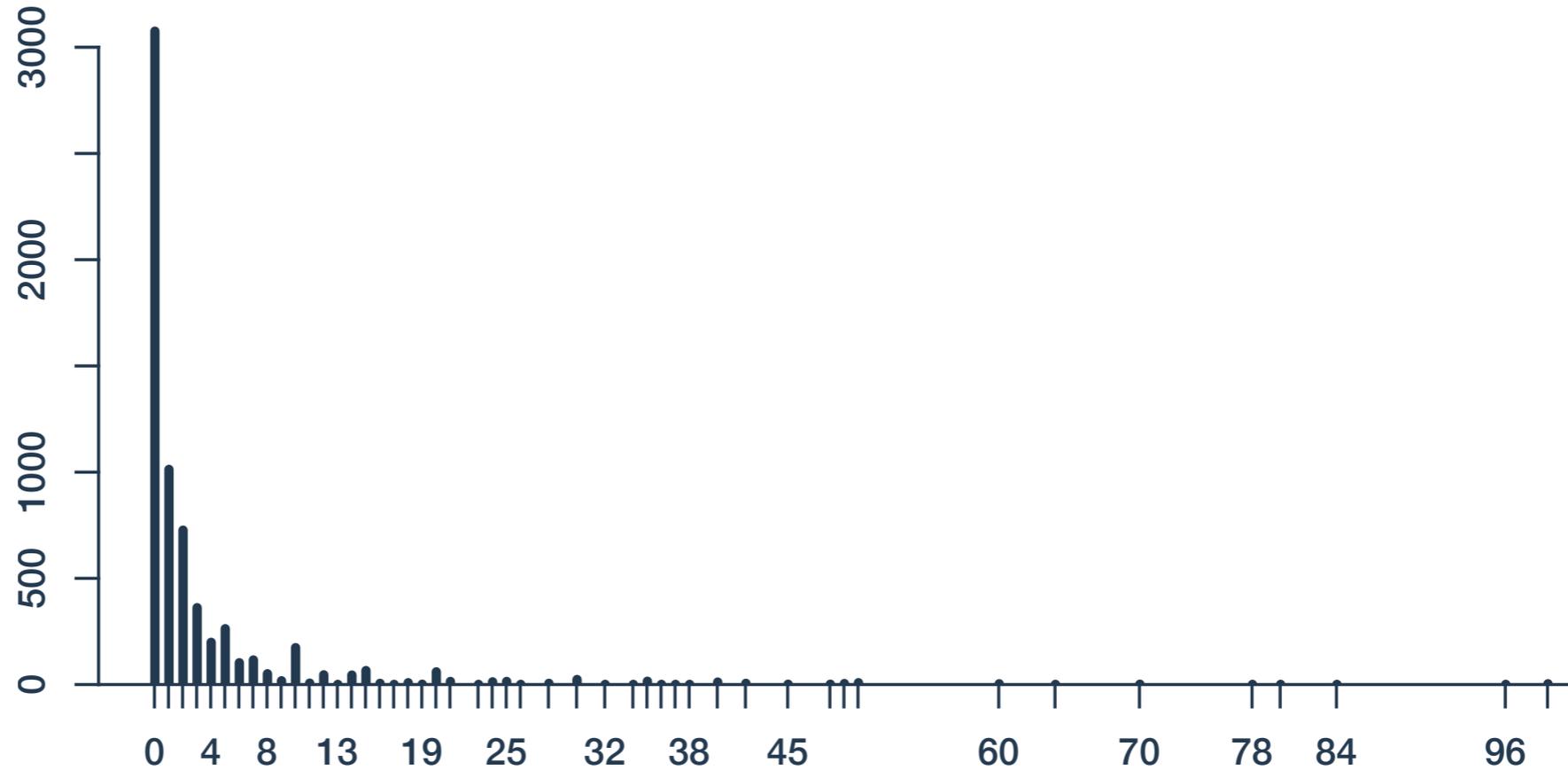
	<i>Mean</i>	<i>90% credible interval</i>		<i>exp(Mean)</i>
<b><math>\alpha</math></b>	0.55	0.50	0.61	1.74
<b><math>\beta</math></b>	0.86	0.80	0.91	2.35
<b><math>\theta</math></b>	8.56	8.09	9.03	—

**$\theta$  measures extra dispersion**

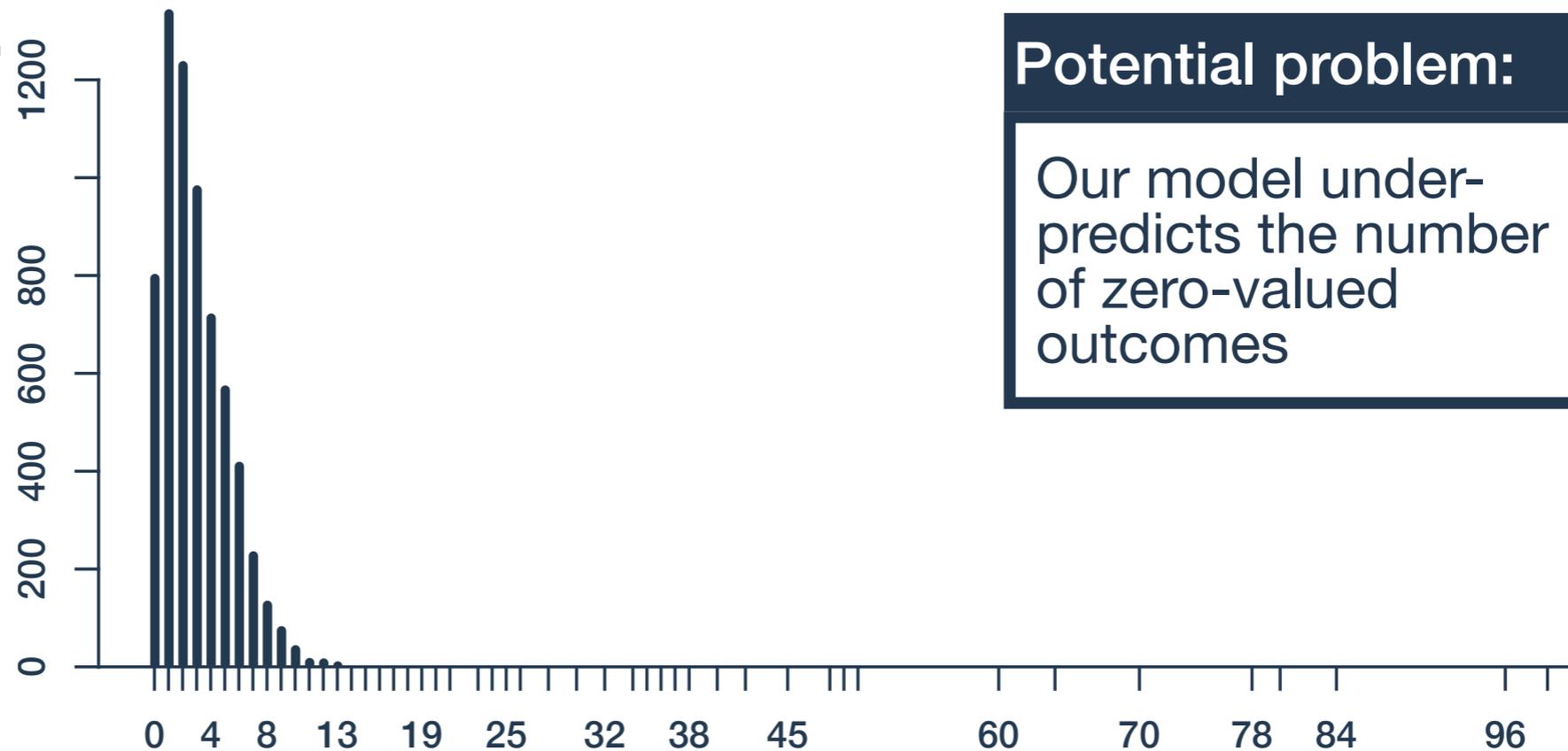


# Zero-inflation

**Actual distribution**



**Posterior predicted distribution (Poisson regression)**



**Potential problem:**

Our model under-predicts the number of zero-valued outcomes

# Zero-inflation

Outcome variable is result of one of two processes

**Either** the student does not own a game console ( $c_i = 1$ ) **or** the student does own a console and plays at some rate  $\lambda_i$  ( $c_i = 0$ ).



$$H_i \begin{cases} = 0 & \text{if } c_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } c_i = 0 \end{cases}$$

# Zero-inflation

Their chance of owning a console is modeled with  $p_i$



$$H_i \begin{cases} = 0 & \text{if } c_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } c_i = 0 \end{cases}$$

$$c_i \sim \text{Bern}(p_i)$$

# Zero-inflation

$p_i$  is modeled as a linear function of family income



$$H_i \begin{cases} = 0 & \text{if } c_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } c_i = 0 \end{cases}$$

$$c_i \sim \text{Bern}(p_i)$$

$$\text{logit}(p_i) = \alpha_p + \beta_p W_i$$

# Zero-inflation

$\lambda_i$  is modeled as a linear function of gender



$$H_i \begin{cases} = 0 & \text{if } c_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } c_i = 0 \end{cases}$$

$$c_i \sim \text{Bern}(p_i)$$

$$\text{logit}(p_i) = a_p + \beta_p W_i$$

$$\log(\lambda_i) = a_\lambda + \beta_\lambda M_i$$

# Zero-inflation

All four parameters  
need priors



$$H_i \begin{cases} = 0 & \text{if } c_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } c_i = 0 \end{cases}$$

$$c_i \sim \text{Bern}(p_i)$$

$$\text{logit}(p_i) = a_p + \beta_p W_i$$

$$\log(\lambda_i) = a_\lambda + \beta_\lambda M_i$$

$$a_p \sim \text{Norm}(0, 1)$$

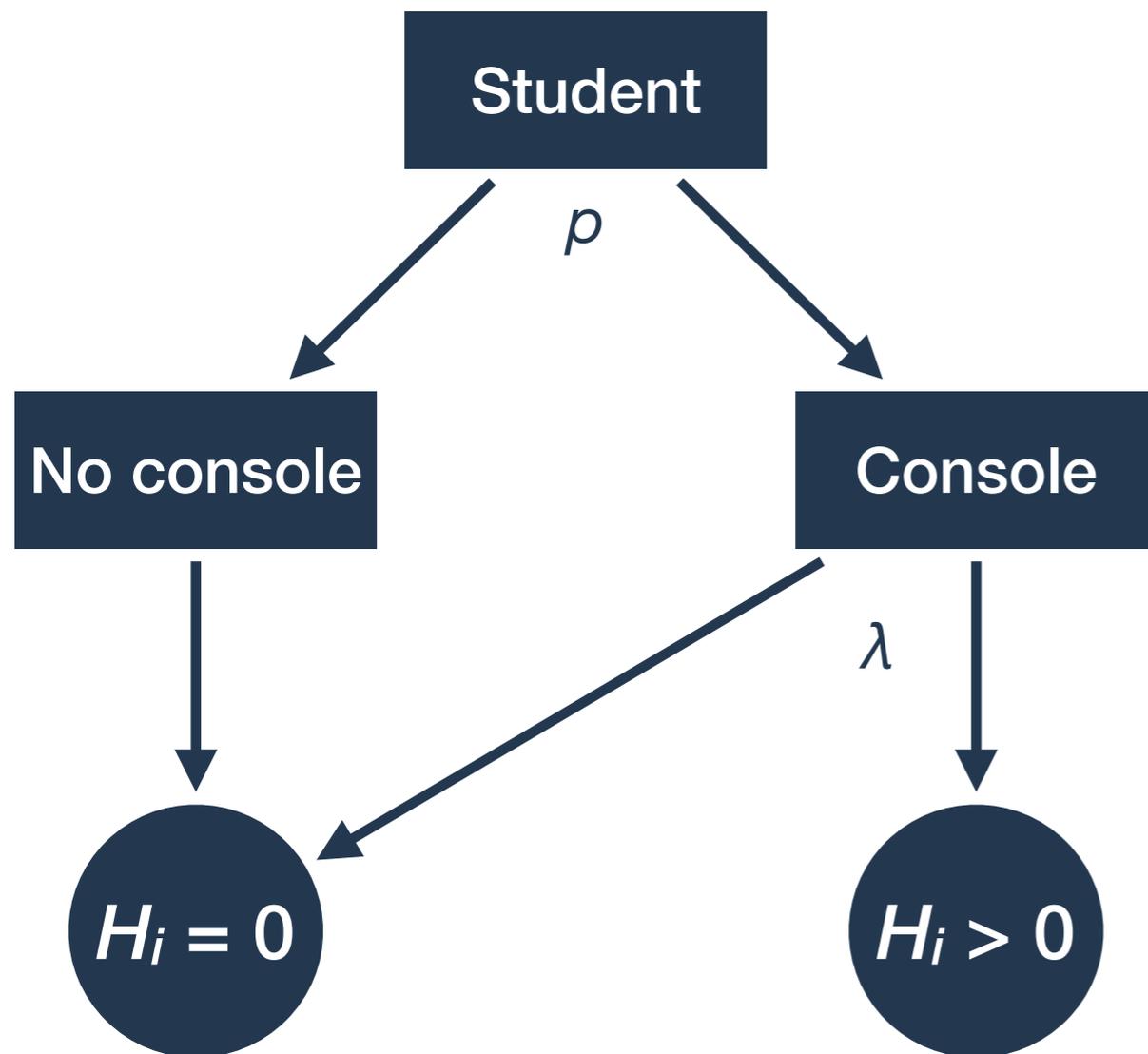
$$\beta_p \sim \text{Norm}(0, 2)$$

$$a_\lambda \sim \text{Norm}(3, 0.5)$$

$$\beta_\lambda \sim \text{Norm}(0, 0.3)$$

# Zero-inflation

Data story:



$$H_i \begin{cases} = 0 & \text{if } c_i = 1 \\ \sim \text{Pois}(\lambda_i) & \text{if } c_i = 0 \end{cases}$$

$$c_i \sim \text{Bern}(p_i)$$

$$\text{logit}(p_i) = a_p + \beta_p W_i$$

$$\log(\lambda_i) = a_\lambda + \beta_\lambda M_i$$

$$a_p \sim \text{Norm}(0, 1)$$

$$\beta_p \sim \text{Norm}(0, 2)$$

$$a_\lambda \sim \text{Norm}(3, 0.5)$$

$$\beta_\lambda \sim \text{Norm}(0, 0.3)$$