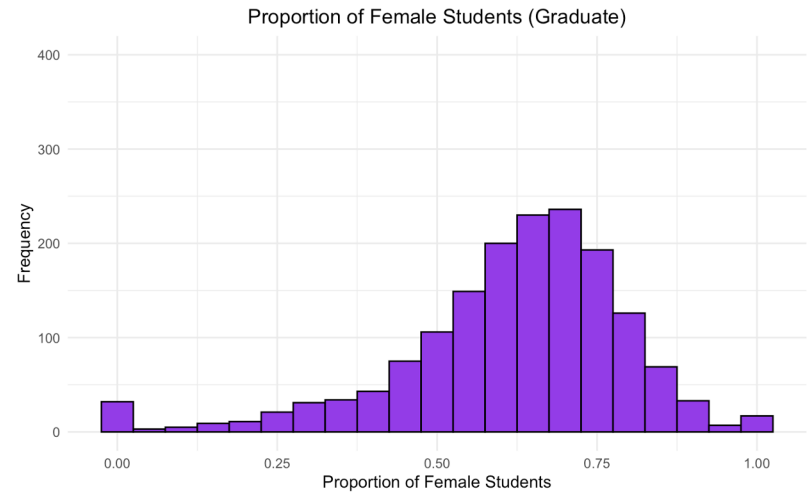
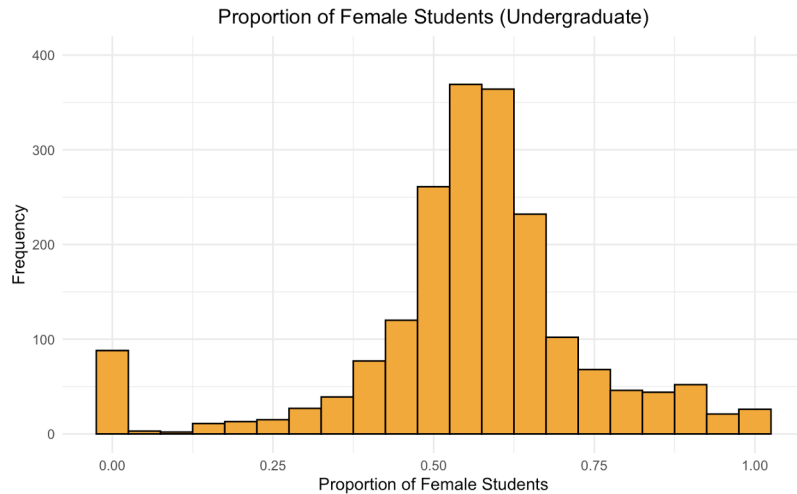


Beta regression

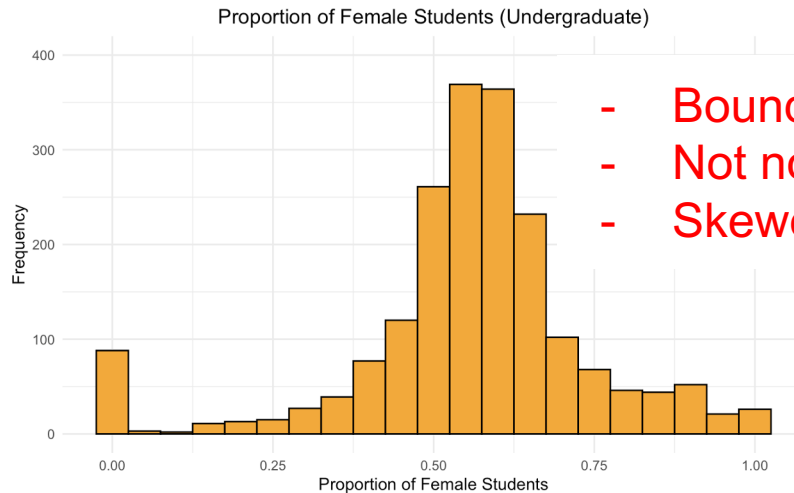
When to use

- Slider scales (opinions, confidence ratings)
- Proportional data (% of women in academia)

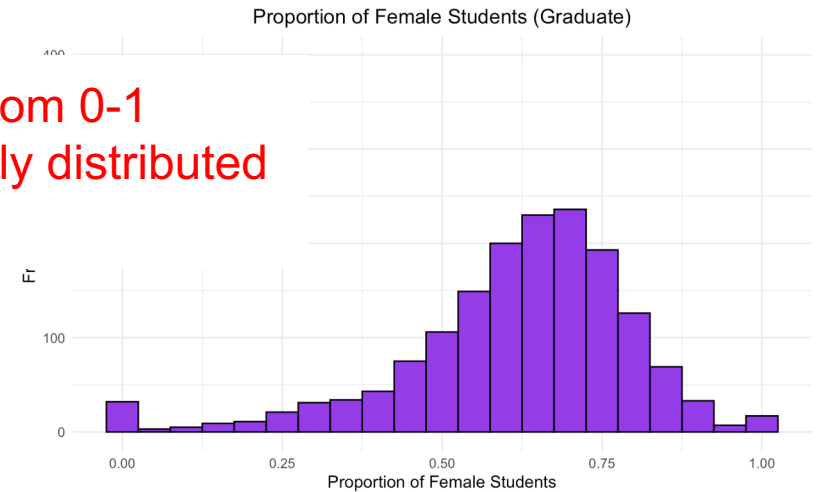


When to use

- Slider scales (opinions, confidence ratings)
- Proportional data (% of women in academia)

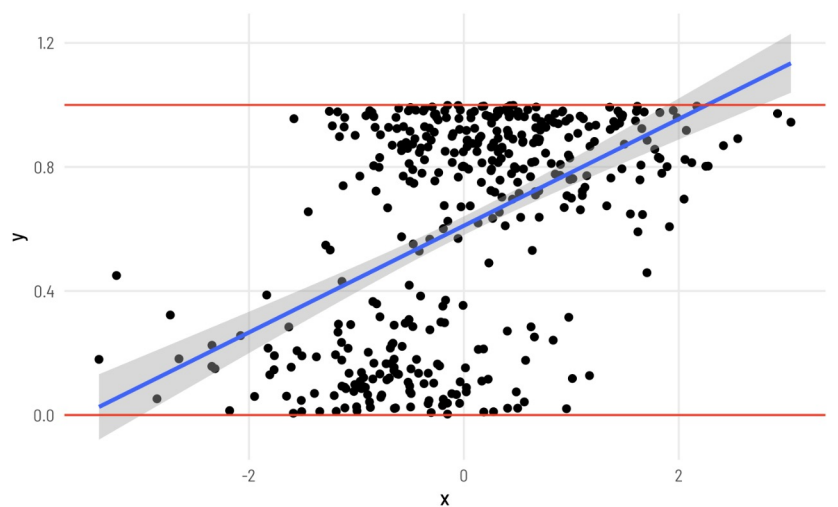


- Bounded from 0-1
- Not normally distributed
- Skewed



Solutions

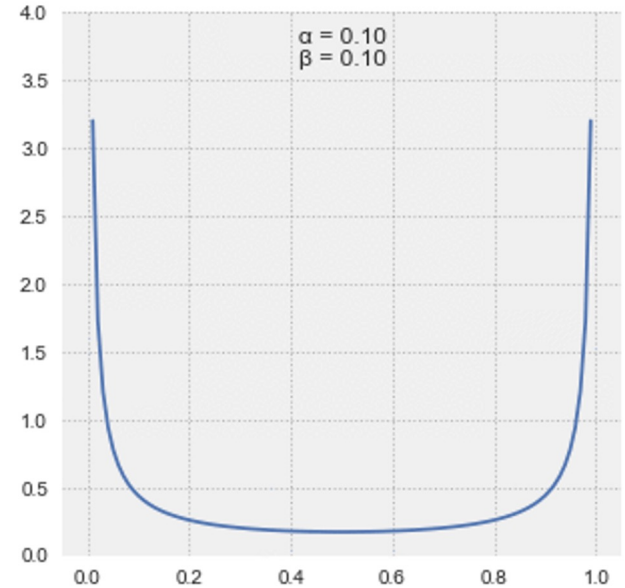
- Linear probability model
 - Just ordinary least squares (OLS) applied to a proportional outcome
 - Commonly used, but estimates can go out of the boundaries.
- Fractional logistic model
 - `glm(..., family = binomial(link = "logit"))`
 - Warning: using `family = binomial()` with a non-binary outcome variable



Beta regression

Beta - the use of the **Beta distribution** for the response variable

- Naturally limited to numbers between 0 and 1 (but doesn't include 0 or 1).
- Extremely flexible distribution and can take all sorts of different shapes and forms
- **A probability distribution of probabilities**

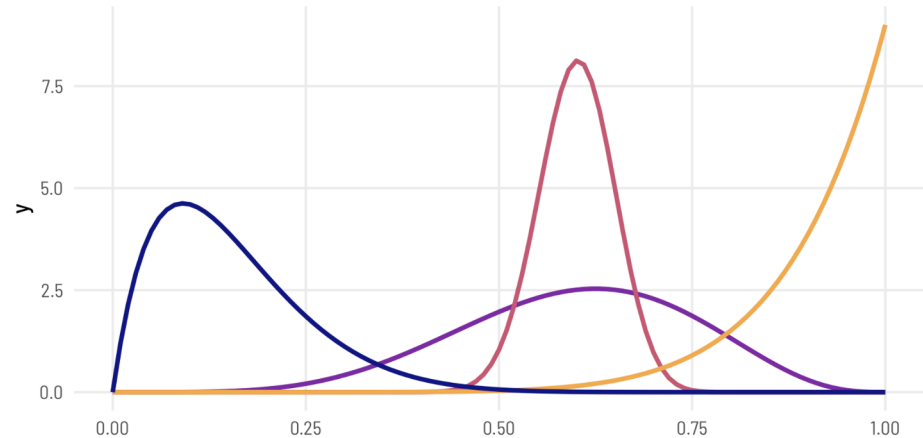


Beta distribution

- Two parameters: a /shape1, b / shape 2
 - E.g., a = number of women, b = number of men

- Mean $\mu = \frac{a}{a + b}$

- Precision $\phi = a + b$



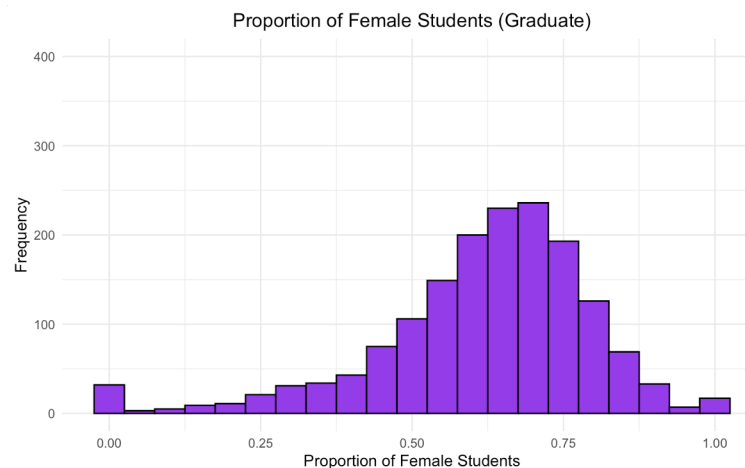
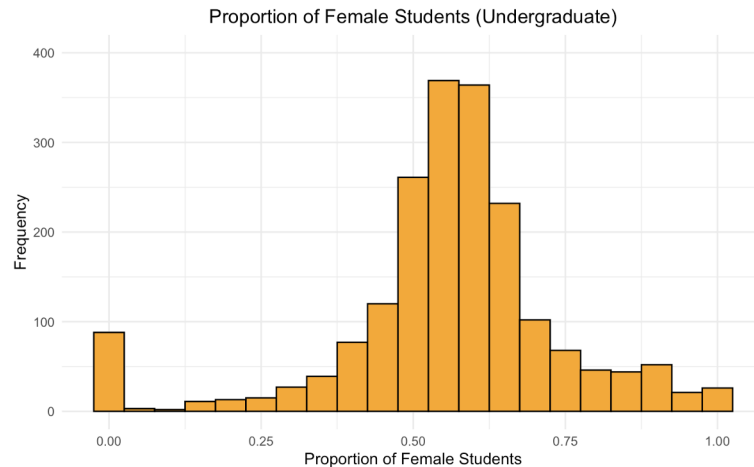
— Beta(shape1 = 2, shape2 = 11) — Beta(shape1 = 60, shape2 = 40)
— Beta(shape1 = 6, shape2 = 4) — Beta(shape1 = 9, shape2 = 1)

Beta regression

Distributional regression - modeling μ and ϕ , instead of slope and intercept

- $0 \rightarrow 0.0001$; $1 \rightarrow 0.9999$

```
model_beta <- betareg(prop.female ~ level |  
level, data = df, link = "logit")
```

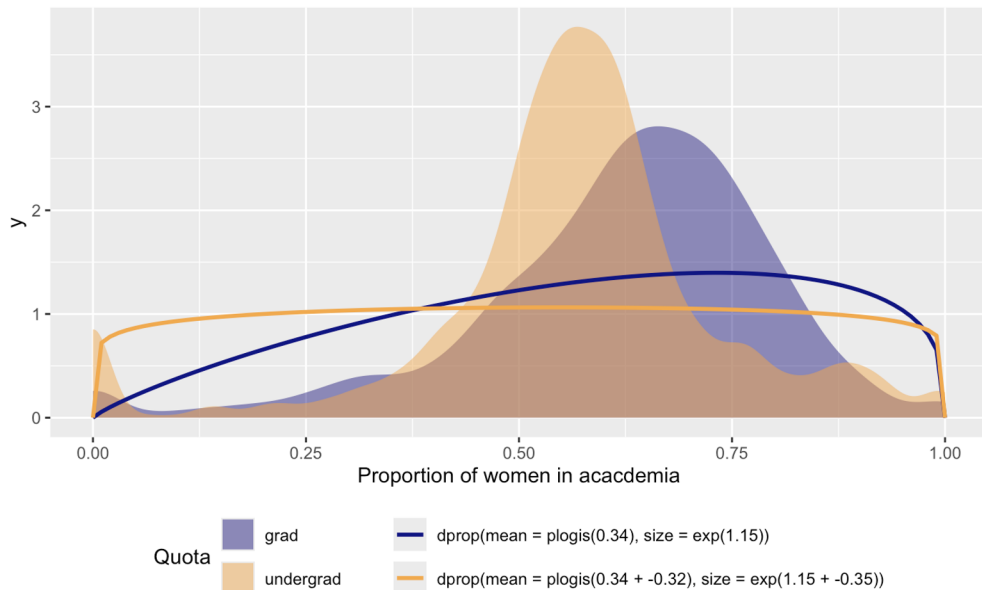


Beta regression

Distributional regression - modeling μ and Φ , instead of slope and intercept

- $0 \rightarrow 0.0001$; $1 \rightarrow 0.9999$

```
- model_beta <- betareg(prop.female ~ level |  
  level, data = df, link = "logit")
```

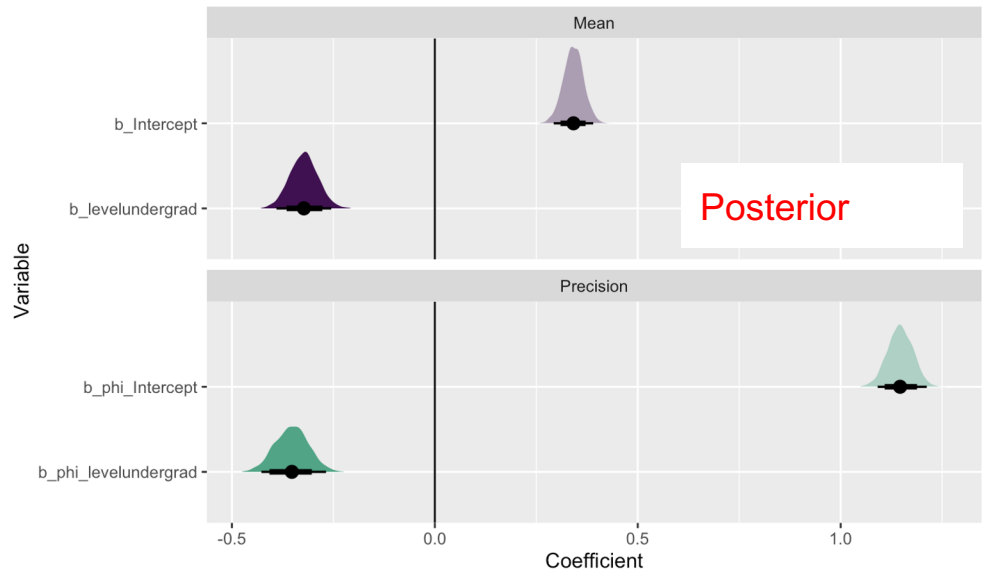


```
> tidy(model_beta)  
# A tibble: 4 × 6  
  component term          estimate std.error statistic p.value  
  <chr>      <chr>          <dbl>    <dbl>    <dbl>    <dbl>  
1 mean      (Intercept)    0.376    0.0226    16.6  4.10e-62  
2 mean      levelundergrad -0.297    0.0320    -9.28 1.69e-20  
3 precision (Intercept)    1.34     0.0316    42.4  0  
4 precision levelundergrad -0.334    0.0419    -7.97 1.57e-15
```


Beta regression - Bayesian

Treat μ and Φ as distributions to model uncertainty

```
model_beta_bayes <- brm(bf(prop.female.posi  
~ level, phi ~ level), data = df, family =  
Beta(), chains = 4, iter = 2000, warmup =  
1000, cores = 4)
```



80% and 95% credible intervals shown in black

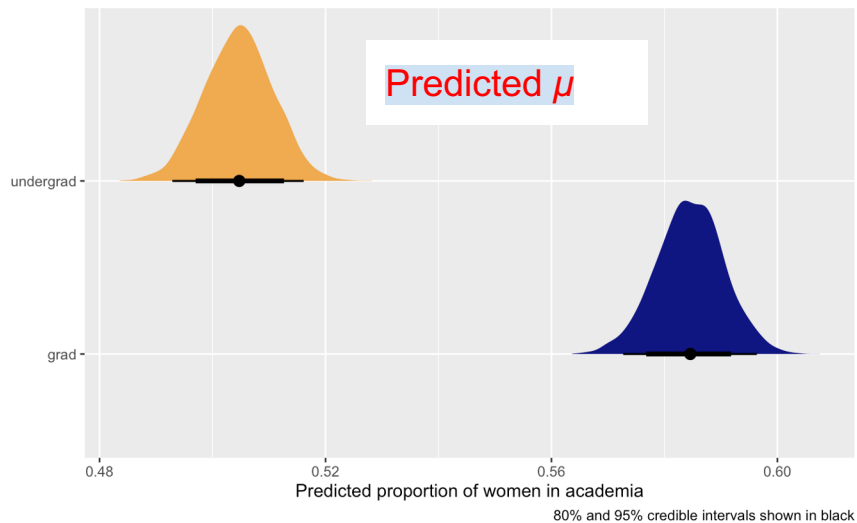
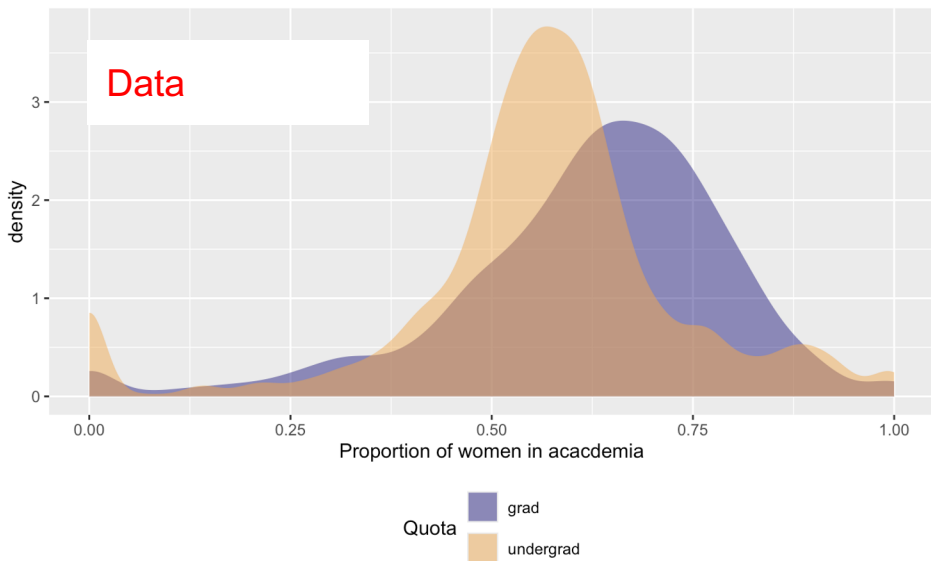
Population-Level Effects:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	0.34	0.02	0.29	0.39	1.00	4432	3088
phi_Intercept	1.15	0.03	1.09	1.21	1.00	4025	3017
levelundergrad	-0.32	0.03	-0.39	-0.25	1.00	3939	2676
phi_levelundergrad	-0.35	0.04	-0.43	-0.27	1.00	4384	3092

Beta regression - Bayesian

Treat μ and ϕ as distributions to model uncertainty

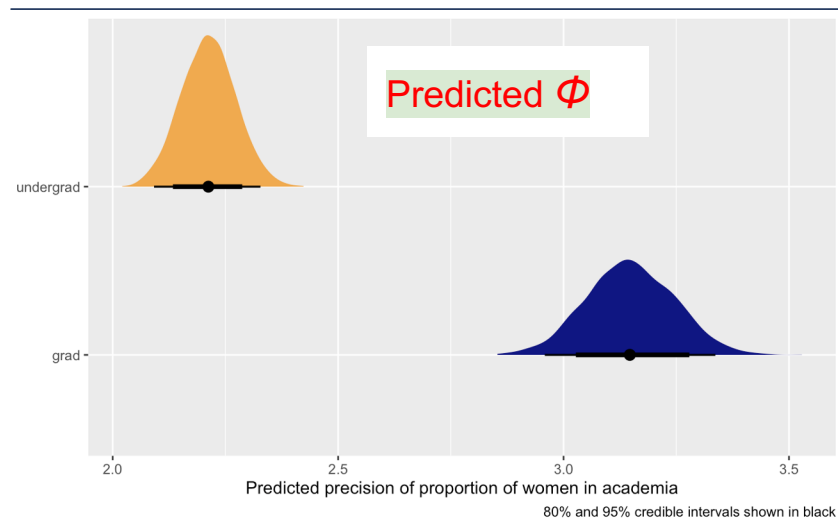
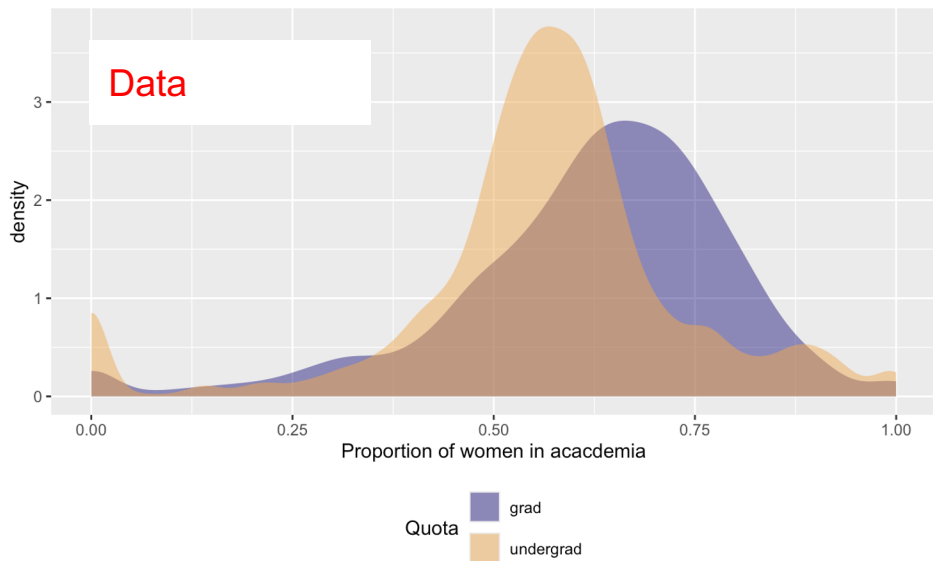
```
model_beta_bayes <- brm(bf(prop.female.posi ~ level, phi ~ level), data = df, family = Beta(), chains = 4, iter = 2000, warmup = 1000, cores = 4)
```



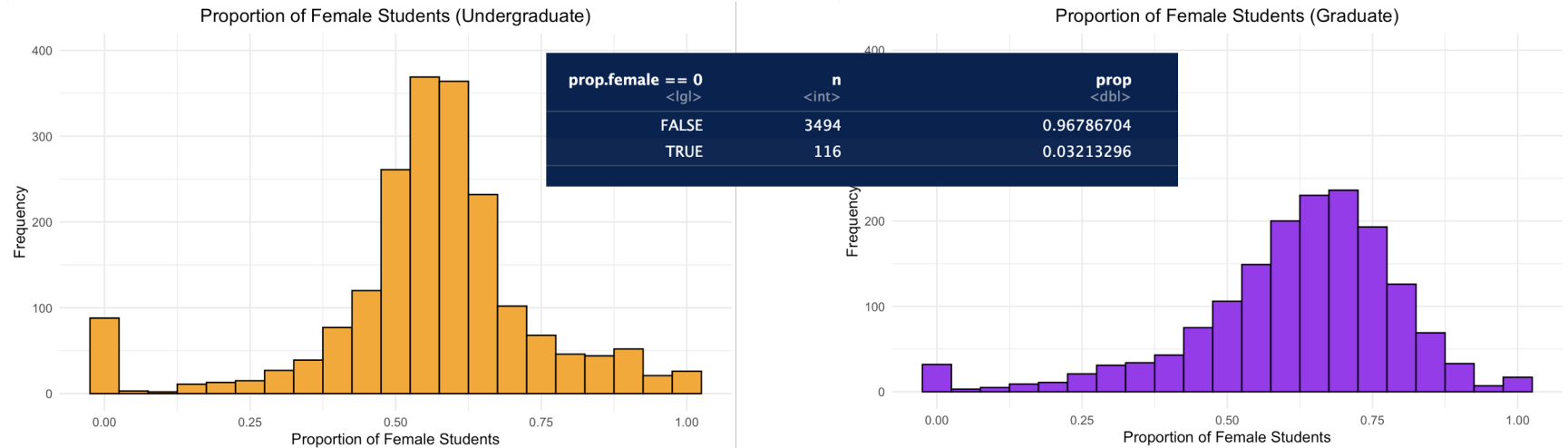
Beta regression - Bayesian

Treat μ and ϕ as distributions to model uncertainty

```
model_beta_bayes <- brm(bf(prop.female.posi ~ level, phi ~ level), data = df, family = Beta(), chains = 4, iter = 2000, warmup = 1000, cores = 4)
```



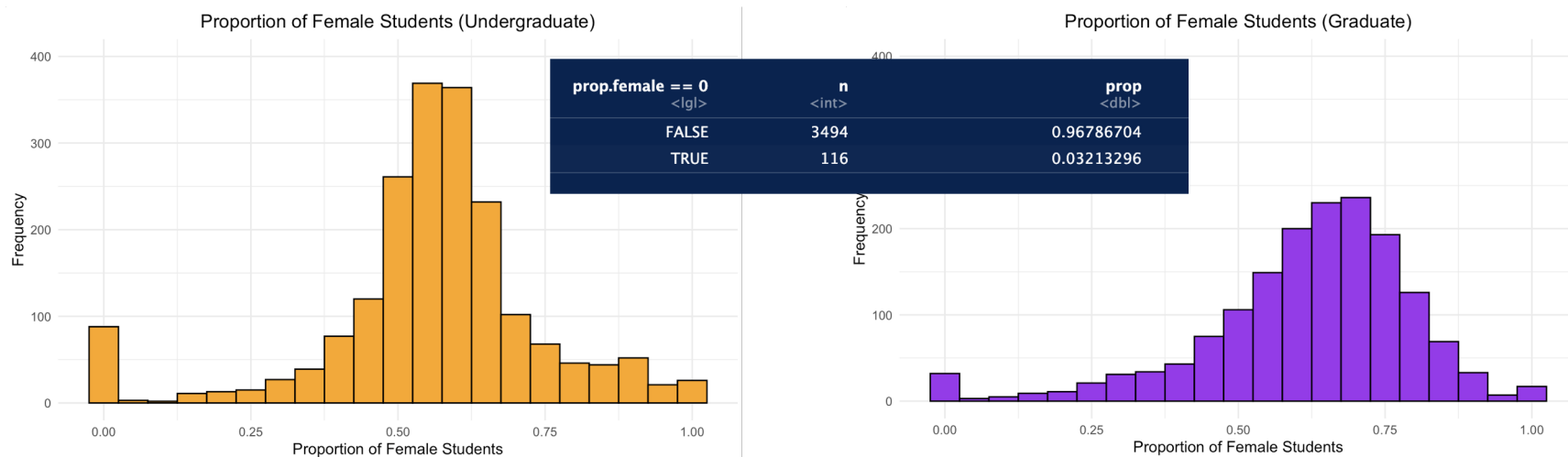
Zero-inflated beta regression



Zero-inflated beta regression

Modelling a mixture of data-generating processes:

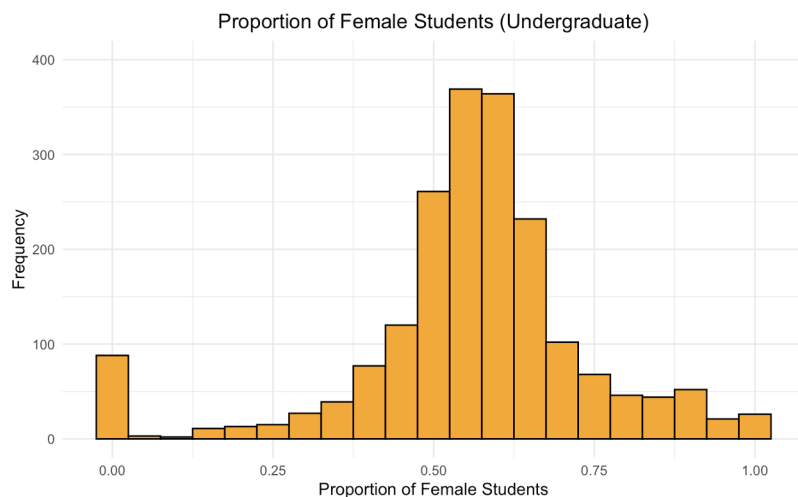
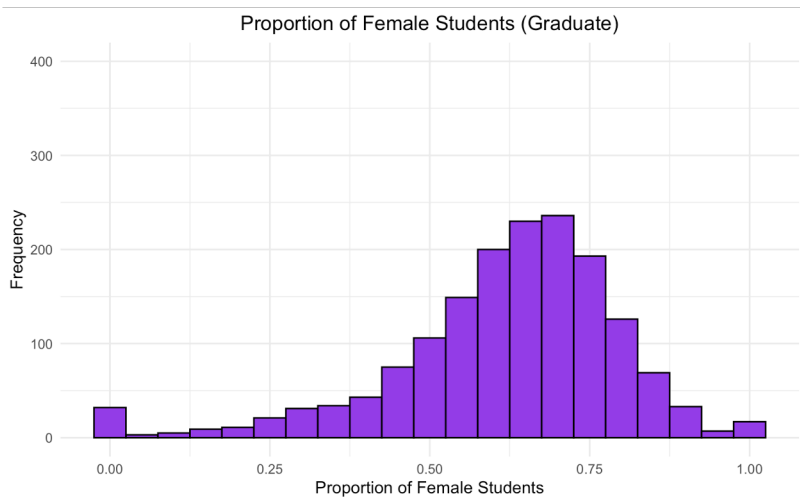
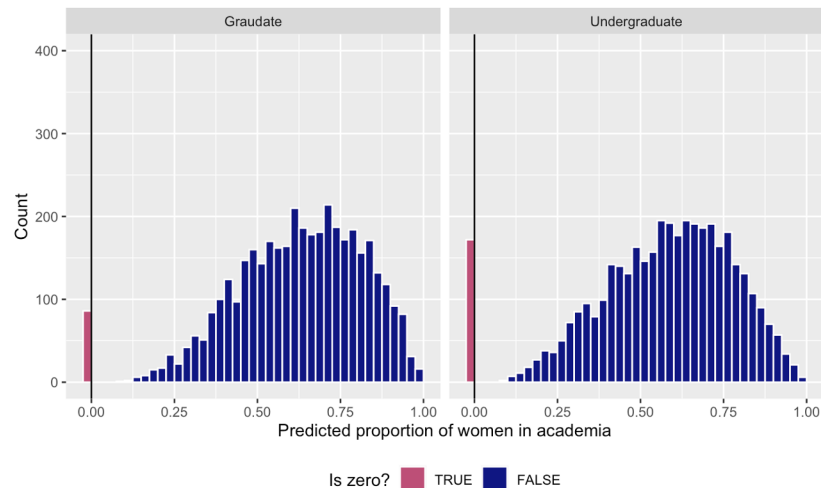
1. A **logistic regression model** that predicts if an outcome is 0 or not, defined by α
2. A **beta regression model** that predicts if an outcome is between 0 and 1 if it's not zero (μ and ϕ)



Zero-inflated beta regression

Modeling α , μ and ϕ

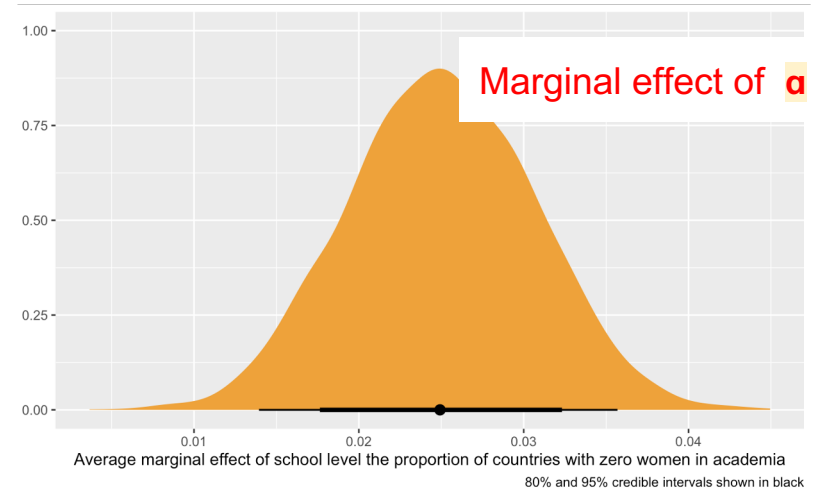
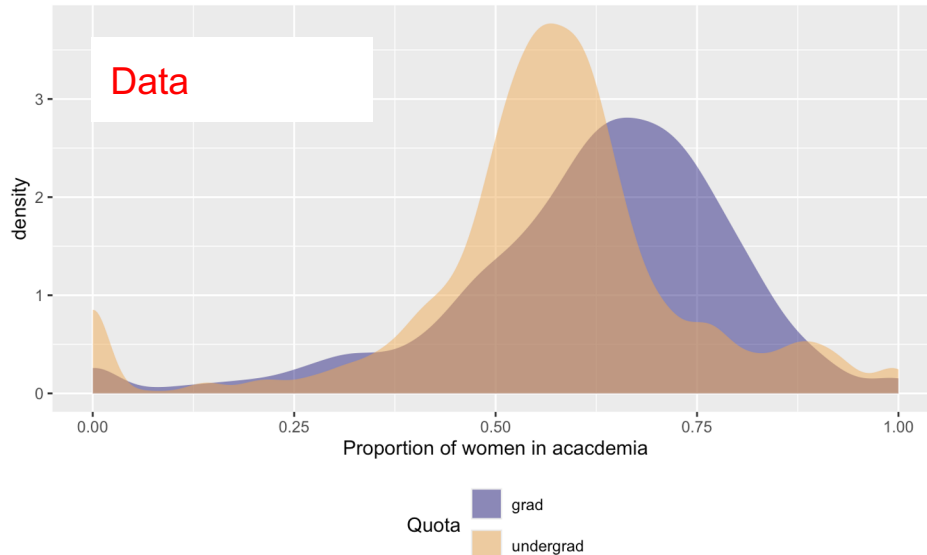
- $0 \rightarrow 0$; $1 \rightarrow 0.9999$
- ```
model_beta_zi <- brm(bf(prop.female ~
level, phi ~ level, zi ~ level), data = df,
family = zero_inflated_beta(), chains = 4,
iter = 2000, warmup = 1000, cores = 4)
```



# Zero-inflated beta regression

## Modeling $\alpha$ , $\mu$ and $\phi$

```
- model_beta_zi <- brm(bf(prop.female ~ level, phi ~ level, zi ~ level), data = df, family =
zero_inflated_beta(), chains = 4, iter = 2000, warmup = 1000, cores = 4)
```



# Zero-one-inflated beta regression

Zero-inflated beta regression:

1. A **logistic regression model** that predicts if an outcome is 0 or not, defined by  $\alpha$
2. A **beta regression model** that predicts if an outcome is between 0 and 1 if it's not zero ( $\mu$  and  $\phi$ )

Zero-one-inflated beta regression:

1. A **logistic regression model** that predicts if an outcome is extreme (0 or 1) or not, defined by  $\alpha$
2. A **logistic regression model** that predicts if the extreme outcome is 1, defined by  $\gamma$
3. A **beta regression model** that predicts if an outcome is between 0 and 1 if it's not zero ( $\mu$  and  $\phi$ )



# Zero-one-inflated beta regression

Modeling  $\alpha$ ,  $\gamma$ ,  $\mu$  and  $\Phi$

-  $0 \rightarrow 0$ ;  $1 \rightarrow 1$

```
model_beta_zi <- brm(bf(prop.female ~ level, phi ~ level, zoi
~ level, coi ~ level), data = df, family =
zero_inflated_beta(), chains = 4, iter = 2000, warmup = 1000,
cores = 4)
```

