Lying for Profit: An Empirical Evaluation of Antecedents of Dishonesty

Michael Geden & Amanda Young

Introduction

- **Counterproductive work behaviors** (CWB): volitional acts that harm (or intend to harm) an organization or its members (Spector et al., 2006)
  - Different CWBs have different antecedents; we focused on **theft**
- Theft costs organizations a lot of money, BUT it is hard to measure because people are motivated to lie on self-report measures
  - We created an empirical proxy for organizational theft in which participants could earn more money by lying
    - Similar to getting paid more for lying on a time card

Antecedents:
- Temporary cognitions and more stable dispositional traits both influence behaviors
- **Moral disengagement**: dispositional propensity to rationalize immoral action as just to avoid guilt (Bandura, 1986)
- **Cognitive Dissonance:** holding inconsistent cognitions creates an unpleasant tension that individuals seek to reduce (Festinger, 1957)
  - "I am a good person" + "I stole something" + "Stealing is bad and good people don't do it" = dissonance
  - **Hypocrisy:** underlines induces cognitive dissonance; after committing a transgression, individuals act in a compensatory moral manner to reduce dissonance (Greene & Low, 2014)
  - **Moral Licensing:** reduces cognitive dissonance; after committing a moral behavior, individuals are more likely to engage in immoral behavior (Jordan, Mullen, & Murnigham, 2011)

- **The current study** tested the whether moral disengagement and either inducing (hypocrisy) or reducing (moral licensing) cognitive dissonance would influence individuals' response to an empirical proxy for theft.

Hypotheses

H1: Moral licensing will be positively related to theft.

H2: Hypocrisy will be negatively related to theft.

H3: Moral disengagement will be positively related to theft.

Experimental Method/Data

Primary Dataset:
- Gave survey to 138 Mechanical Turk workers
- Between-subjects design with 3 conditions:
  - Control: no dissonance manipulation baseline
  - Hypocrisy: increase dissonance by writing ramifications of theft essay followed by describing a time you stole in the past
  - Moral licensing: decrease dissonance by writing ramifications of theft essay followed by describing a time you were ethical in the past
- Moral disengagement measure via self-report assessment
- **Empirical theft proxy**
  - Given an impossible word search supposedly containing "Latin Names for Plants" and offered a bonus payment for every word they self-reported finding
  - There were actually no words to find
  - 1 minute time limit to make it seem hard instead of impossible
  - Lying with the intent to profit = any number of words reported above 0

Prior Dataset:
- 503 participants from Mechanical Turk
- Completed same empirical theft proxy, but no measure of antecedents
- Used to create informative priors for the intercept in regression models for primary dataset

Impossible Word Search

```
A K I Y T G Y W W K J I M U V
N O Y S Y F Z W A Q S S G W J
X L C J F F C S M T V R B U Q
V I Z D K P I X A C X C O H C
L G P O I B A Y K K L P F A S
O C B L X O N U D O W I B E X
S U U Z Y X C I L C P R Z X I
G A Q V V I U H C W K A K T Y
G M O H W V D Z W X D T P U G
G R D P C S J C F R X O E H X
L D S C O S N D H J Z P S X I
Z L D Q M D Z R Z Z S E S M M
F Q R C Z O I A T C Q P X E W
Q R P S C P A H G P Y A T D H
H I S Y M L M Q N H J C F E A
```

ALNUS	RHANTERIUM	BUXUS
ASCLEPIAS	GLUTINOSA	TRIFIDA
INCANA	DULCAMARA	LIEX
MALUS	SYMPLOCARPUS	SYRIACA
PRUNUS	PLANTANUS	DAUCUS
RUDBECKIA	POMIFERA	LYONOTHAMNUS
SOLANIUM	HIRTA	

Models

Three Types of Models:

1. Poisson

$Y_i \sim Poisson(\lambda_i)$

$\log(\lambda_i) = \beta_0 + \beta_1*Licensing_i + \beta_2*Hypocrisy_i + \beta_3*Moral\ Disengagement_i$

2. Overdispersed Poisson

$Y_i \sim Poisson(\lambda_i)$

$\log(\lambda_i) = \beta_0 + \beta_1*Licensing_i + \beta_2*Hypocrisy_i + \beta_3*Moral\ Disengagement_i + \gamma_i$

$\gamma_i \sim Normal(0, \sigma^2)$

3. Negative Binomial

$Y_i \sim NegativeBinomial(p_i, r)$

$p_i = \frac{r}{r+\lambda_i}$

$r \sim Uniform(0,50)$

$\log(\lambda_i) = \beta_0 + \beta_1*Licensing_i + \beta_2*Hypocrisy_i + \beta_3*Moral\ Disengagement_i$

Priors for Intercept:
- Licensing & Hypocrisy are dummy-coded indicators of condition, and moral disengagement was mean-centered, so β_0 represents base degree of lying
- Prior dataset used to create informative priors for intercept (β_0)
  - Found mean (μ_{prior}) and variance (σ^2_{prior}) for posterior distribution of the β_0
  - Run for Poisson, Overdispersed Poisson, and Negative Binomial
- 3 different priors used for β_0
  1. Uninformative: $\beta_0 \sim Normal(0, 1000)$
  2. Weak Prior: $\beta_0 \sim Normal(\mu_{prior}, \sigma^2_{prior}*4)$
  3. Strong Prior: $\beta_0 \sim Normal(\mu_{prior}, \sigma^2_{prior})$

Uniformative Slope Priors:

$\beta_1 \sim Normal(0, 1000)$

$\beta_2 \sim Normal(0, 1000)$

$\beta_3 \sim Normal(0, 1000)$

Analysis Implementation

- All analyses used JAGs via R
- 3 Markov chains
- Burn-in = 15,000 iterations
- 20,000 iterations per chain
- Trace plots and Gelman–Rubin diagnostic indicated convergence
- Minimum effective sample size > 2,000 for all parameters

Model Selection

10-fold Cross Validation:

Poisson:

β_0 Prior	MSE	Bias	Average SD	Coverage
Uninformative	14.26	-0.02	1.17	0.86
Weak	14.12	0.07	1.20	0.85
Strong	14.18	0.14	1.23	0.86

Overdispersed Poisson:

β_0 Prior	MSE	Bias	Average SD	Coverage
Uninformative	28677.87	38.80	2333.55	0.95
Weak	645.60	10.00	511.42	0.95
Strong	438.27	6.75	256.03	0.94

Negative Binomial:

β_0 Prior	MSE	Bias	Average SD	Coverage
Uninformative	57.04	1.56	39.15	0.95
Weak	55.33	1.83	20.85	0.97
Strong	143.85	3.11	30.79	0.98

DIC:

Penalized Deviance:

Model	Strong	Weak	Uninformative
Poisson	741.2	739.7	739.8
Overdispersed Poisson	281.1	274.1	266.0
Negative Binomial	365.8	363.4	362.5

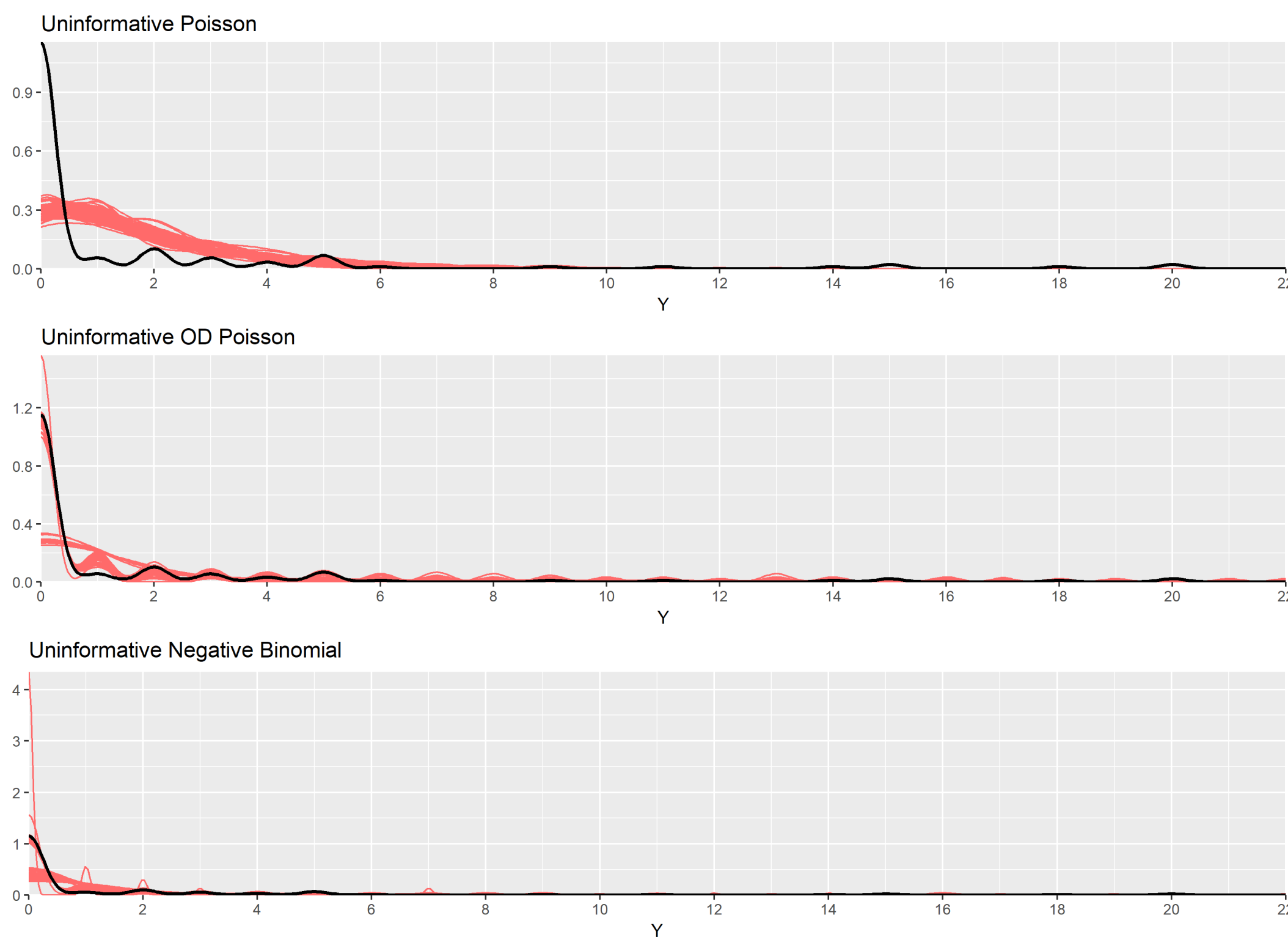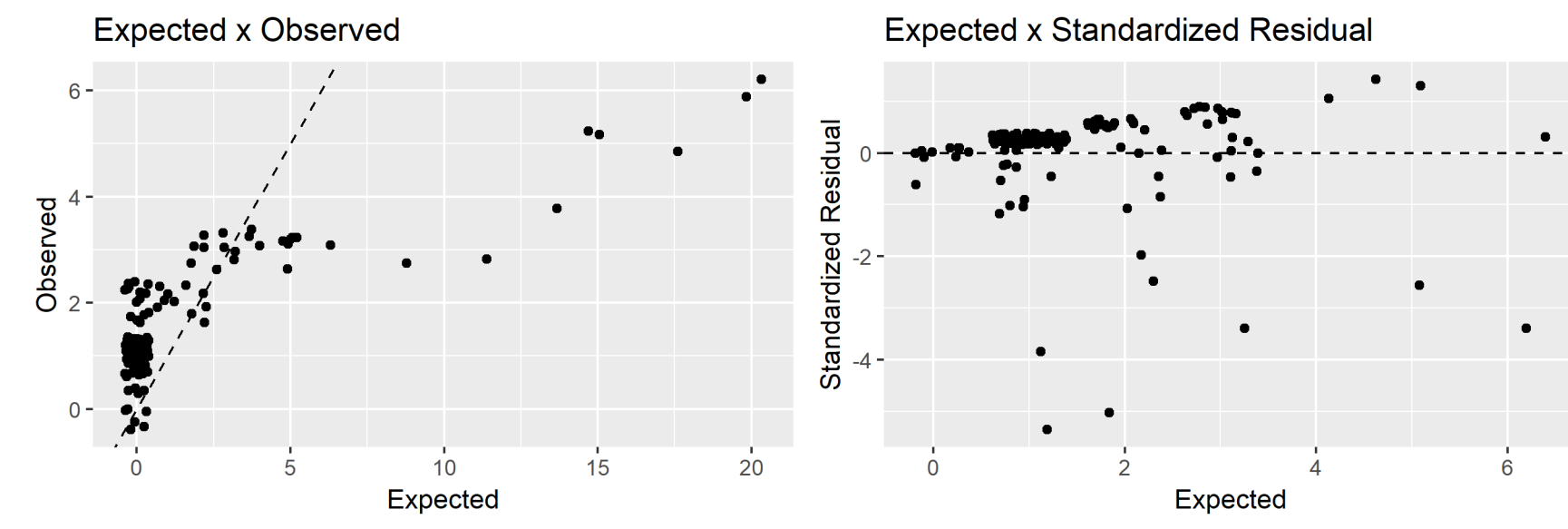## Model Comparison

Actual and Posterior Densities

Figure 1. Actual (black line) and posterior (pink lines) densities for the uninformative β_0 prior. Posterior densities are a sample of 50 draws.
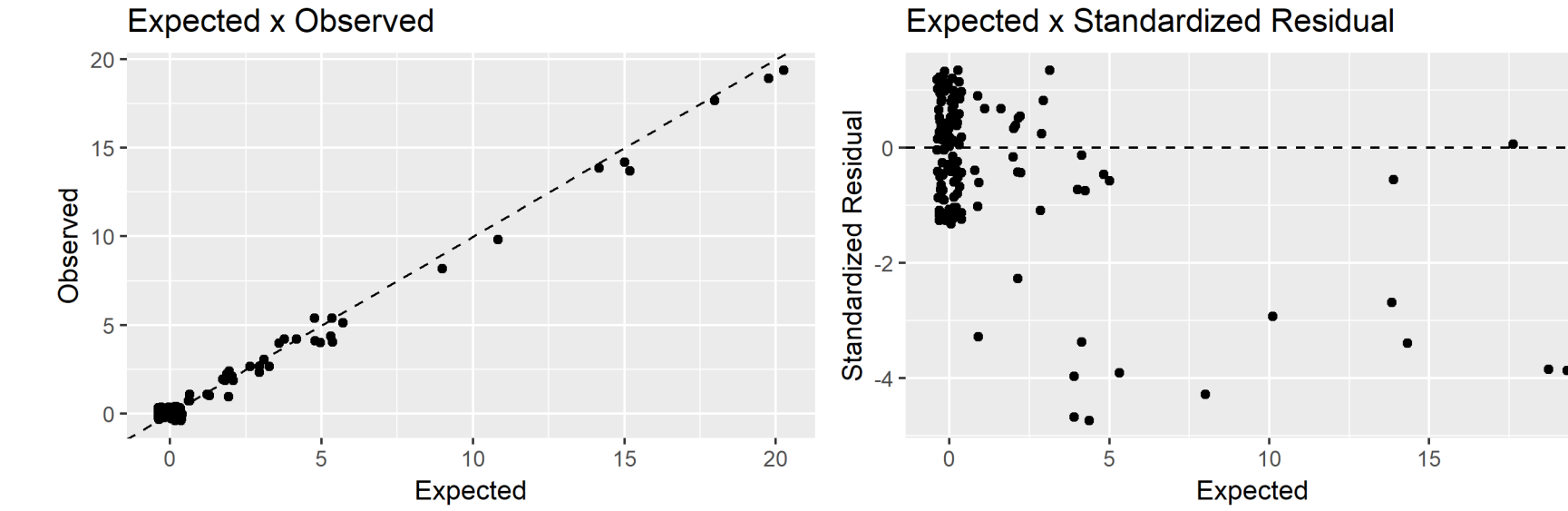- Plots for weak and strong priors were very similar

Residual Plots

Poisson

Overdispersed Poisson

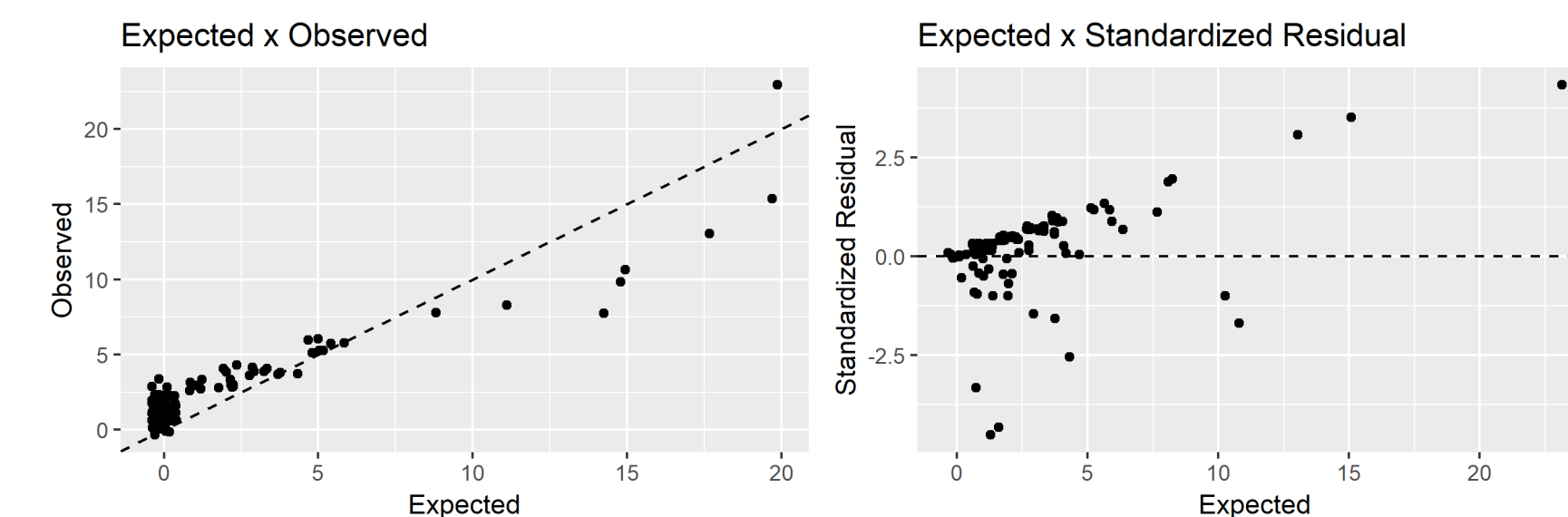**Negative Binomial**

Figure 2. Residual plots for the models using the uninformative β_0 prior.
- Plots for weak and strong priors were very similar

Results

- The Overdispersed Poisson model was chosen based on DIC, similarity of posterior to actual densities, and residual plots
  - Hypotheses were evaluated using Overdispersed Poisson models with uninformative, weak, and strong priors for β_0
- **Hypothesis 1:** Not Supported
  - 95% Credible Sets included 0 for β_1
- **Hypothesis 2:** Not Supported
  - 95% Credible Sets included 0 for β_2
- **Hypothesis 3:** Supported
  - 95% Credible Sets did not include 0 for β_3
  - Mean posterior β_3 values: 1.11 (uninformative), 0.98 (weak), 0.42 (strong)

Conclusions

- Overdispersed Poisson models were preferred to Poisson and Negative Binomial models for this data
- Higher moral disengagement is related to increased magnitude of lying for profit
- Moral licensing and hypocrisy were not related to lying
- Conclusions were not affected by using prior information on base rate
  - Magnitude of moral disengagement effect smaller for stronger priors
- Future research:
  - Create strong feelings of dissonance or consonance
  - Test other cognitive variables
  - Replicate in a field setting
  - Is moral disengagement stable or can it be decreased with training?