Lying for Profit: An Empirical Evaluation of Antecedents of Dishonesty

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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:** 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 work 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

$Y_i \sim Poisson(\lambda_i)$

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

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

3. Negative Binomial

$Y_i \sim \text{NegativeBinomial}(p_i, r)$

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

$r \sim \text{Uniform}(0,50)$

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

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 ($\sigma^2{}_{prior}$) for posterior distribution of the β_0
  - Run for Poisson, Overdispersed Poisson, and Negative Binomial
- 3 different priors used for β_0

1. Uninformative: $\beta_0 \sim \text{Normal}(0, 1000)$
2. Weak Prior: $\beta_0 \sim \text{Normal}(\mu_{prior}, \frac{\sigma^2{}_{prior}}{4})$
3. Strong Prior: $\beta_0 \sim \text{Normal}(\mu_{prior}, \sigma^2{}_{prior})$

Uniformative Slope Priors:

$\beta_1 \sim \text{Normal}(0, 1000)$

$\beta_2 \sim \text{Normal}(0, 1000)$

$\beta_3 \sim \text{Normal}(0, 1000)$

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

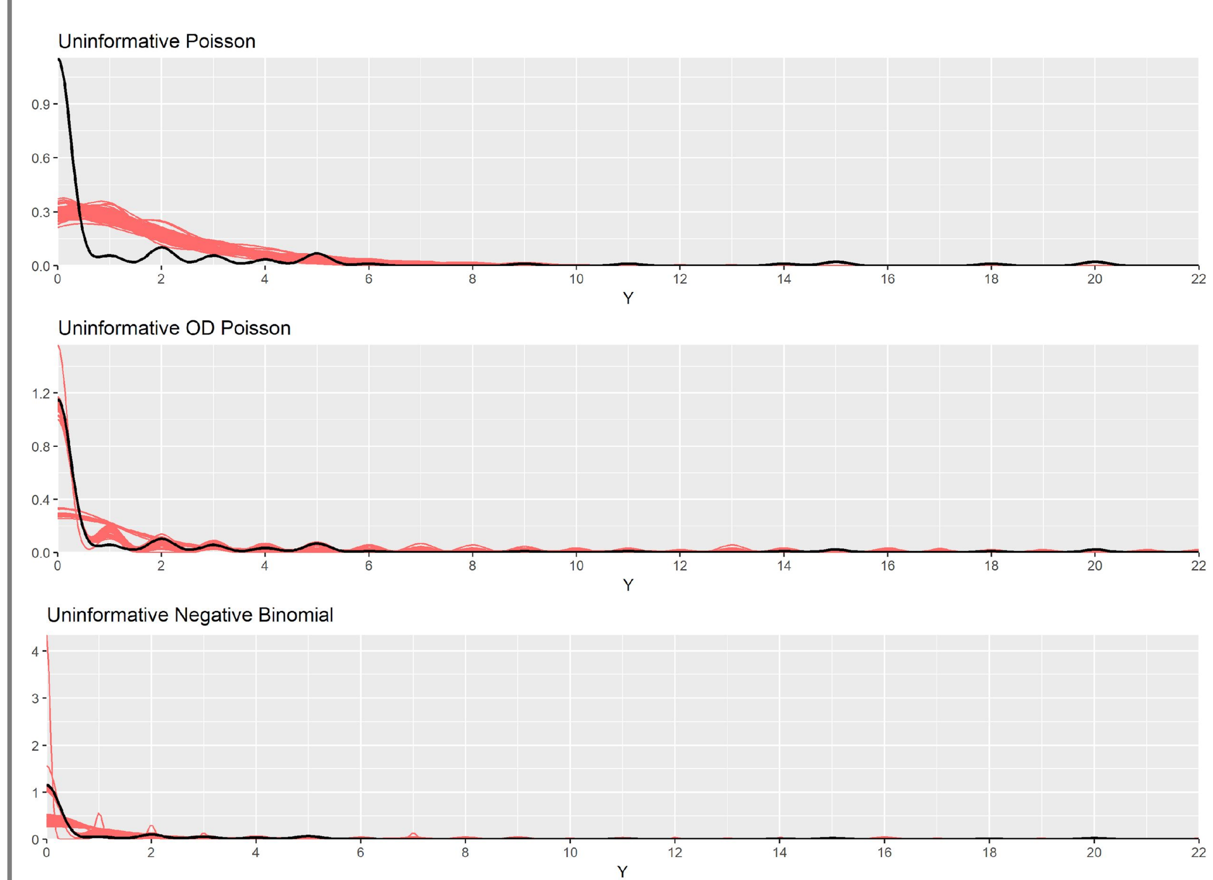
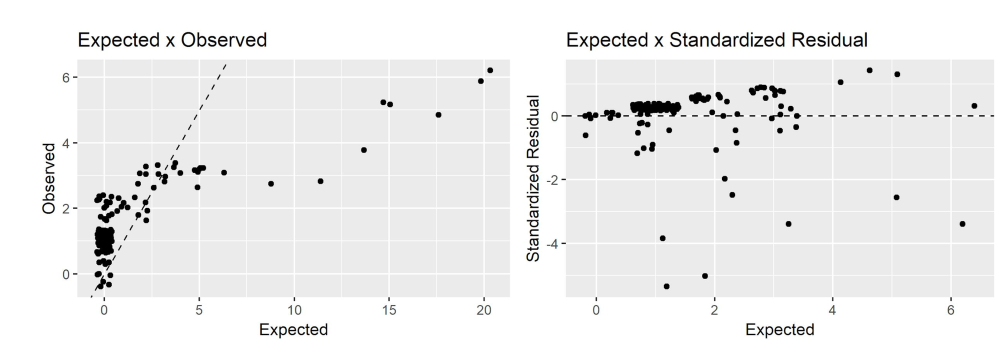


Figure 1. Actual (black line) and posterior (pink lines) densities for the uninformative β_0 prior. Posterior densities are a sample of 50 draws.

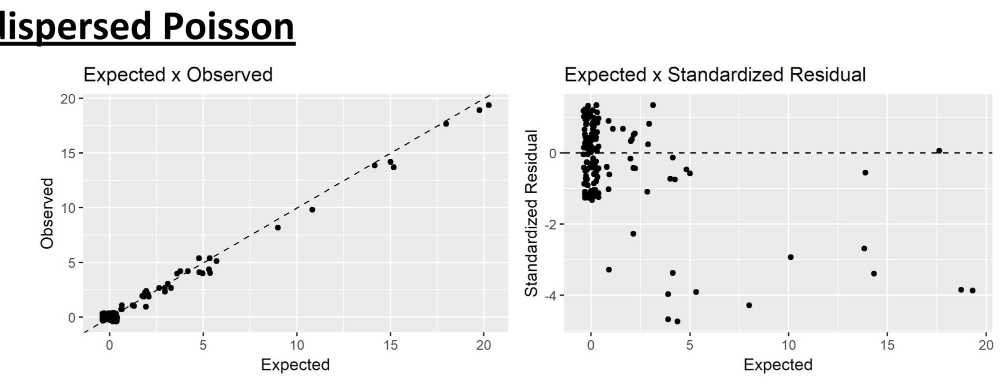
- Plots for weak and strong priors were very similar

Residual Plots

Poisson



Overdispersed Poisson



Negative Binomial

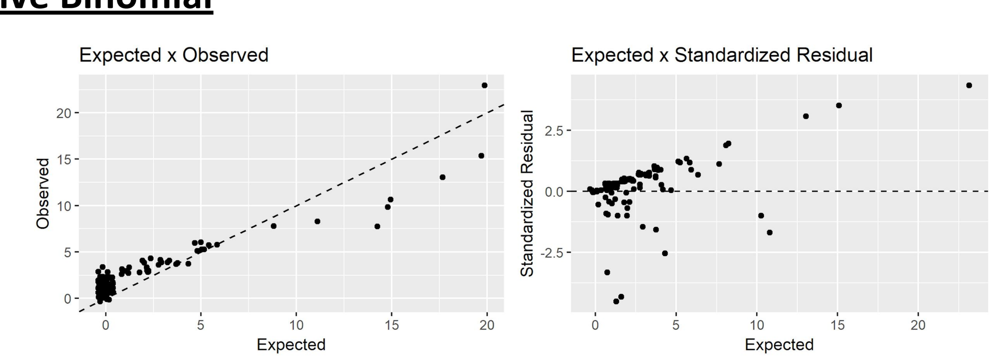


Figure 2. Residual plots for the models using the uninformative β_0 prior.

- 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) ctionary motive

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 decrease with training?