DAILY SLEEP VARIABILITY QUANTIFIED

A RELIABLE AND FLEXIBLE APPROACH

JOSHUA F. WILEY
ELKHART GROUP LTD.
CENTRE FOR PRIMARY CARE AND PREVENTION,
MARY MACKILLOP INSTITUTE FOR HEALTH RESEARCH,
AUSTRALIAN CATHOLIC UNIVERSITY &

BEI BEI
MONASH UNIVERSITY & ROYAL WOMEN'S HOSPITAL

JOHN TRINDER
UNIVERSITY OF MELBOURNE

RACHEL MANBER
STANFORD UNIVERSITY

CONFLICT OF INTEREST DISCLOSURES FOR SPEAKERS

X 1. I do not have any relationships with any entities **producing**, **marketing, re-selling, or distributing** health care goods or services consumed by, or used on, patients, **OR**

☐ 2. I have the following relationships with entities **producing**, **marketing, re-selling, or distributing** health care goods or services consumed by, or used on, patients.

Type of Potential Conflict	Details of Potential Conflict
Grant/Research Support	
Consultant	
Speakers' Bureaus	
Financial support	
Other	

☐ 3. The material presented in this lecture has no relationship with any of these potential conflicts, **OR**

☐ 4. This talk presents material that is related to one or more of these potential conflicts, and the following objective references are provided as support for this lecture:

1.
2.
3.

WHY DAILY SLEEP VARIABILITY MATTERS

Intraindividual variability (IIV) is an individuals' daily fluctuations around her or his own average sleep parameter (e.g., TST, SOL)

- In a systematic review[1, 2] we showed that higher variability is associated with
  - Poorer physical health (e.g., more health conditions)
  - Poorer mental health (e.g., more psychopathology, insomnia)
- Conceptually variability is an important second dimension to the mean

[1]Bei, B., Wiley, J. F., Trinder, J., & Manber, R. (under review). Beyond the mean: A systematic review on the correlates of daily intraindividual variability of sleep/wake patterns.
[2] SLEEP2015 Abstract ID: 0245

CURRENT METHODS FOR QUANTIFYING VARIABILITY

+ Individual standard deviation (ISD) – common, easy

+ Root mean square of successive differences (RMSSD) – common, adjusts for trends

– no accounting for measurement error = biased, underestimates

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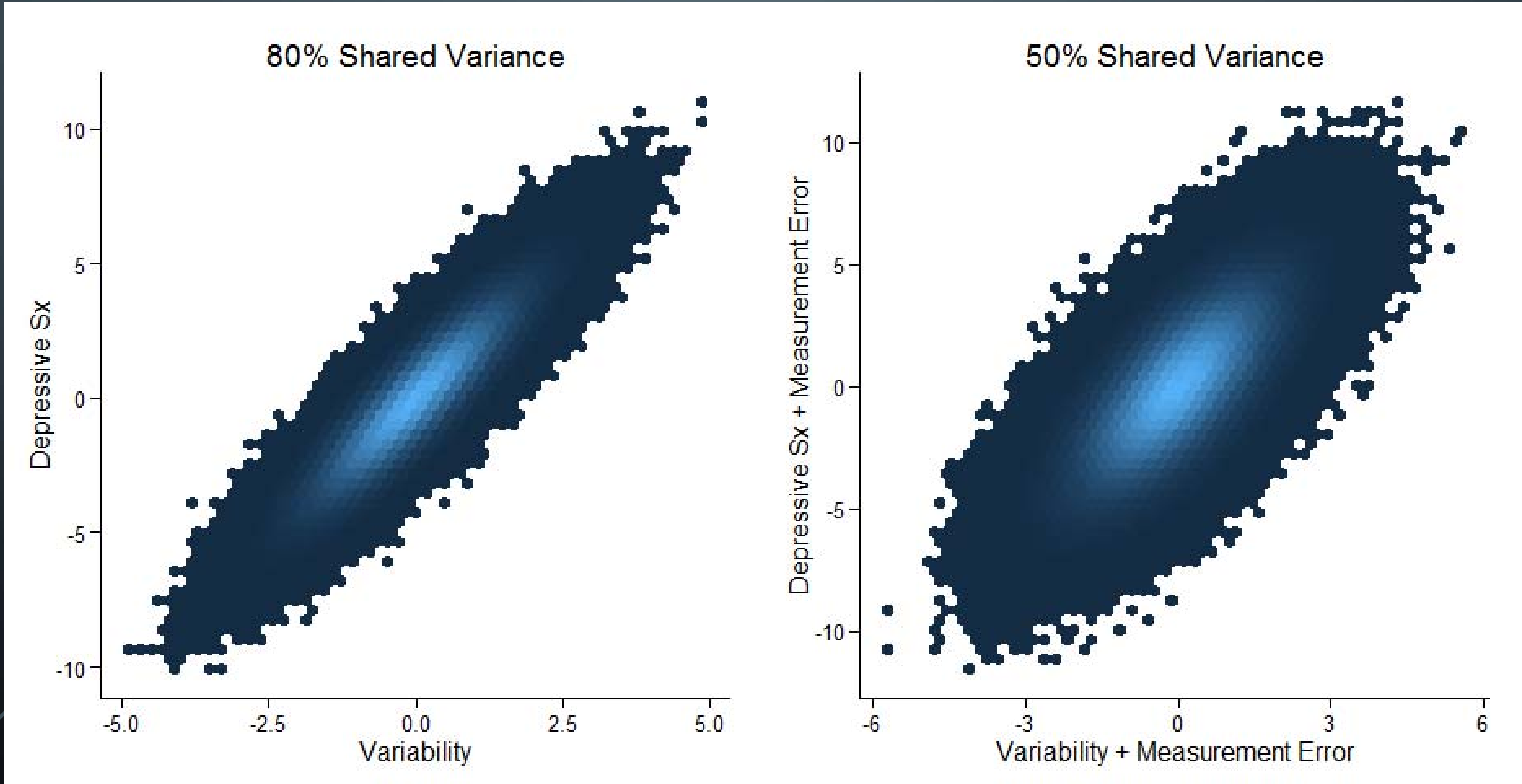

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+ Individual standard deviation (ISD) – common, easy

+ Root mean square of successive differences (RMSSD) – common, adjusts for trends

– no accounting for measurement error = biased, underestimates

– ISD does not account for trends

– RMSSD challenged with missing data

NOVEL BAYESIAN VARIABILITY MODEL (BVM)

To study IIV in sleep want:

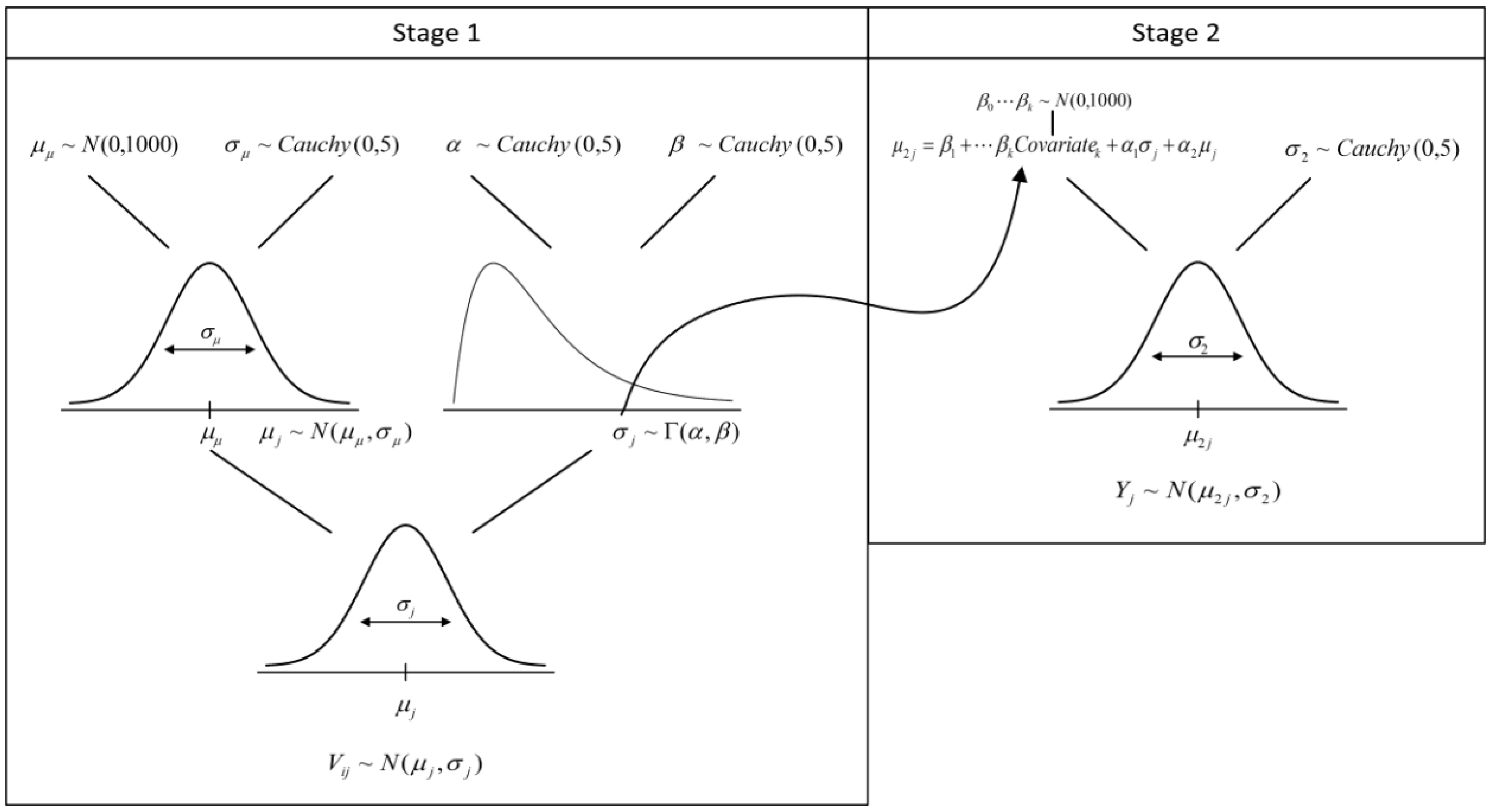
1. Unbiased, correct estimates
2. More power so significant results with smaller sample sizes
3. Account for systematic changes (e.g., gradualling increasing duration following sleep deprivation)
4. Allow for some missing data (e.g., participant forgets to put on actiwatch)

BVM aims to deliver all of these

BVM DETAILS

- Bayesian, probabilistic model
- Assumes a hierarchical structure:
  - Daily sleep nested within individuals
  - Individual means assumed to come from a normal (Gaussian) distribution
  - Individual variability estimates assumed to come from a Gamma distribution
- Estimates of the individual means and variabilities used in a second stage model to predict outcomes (or may be used as outcomes themselves)
- Minimally informative priors used by default
- Estimated using efficient Markov Chain Monte Carlo (MCMC) sampling via the No-U-Turn Sampler and Hamiltonian Monte Carlo

BVM DETAILS



Stage 1
Stage 2
$\mu_\mu \sim N(0,1000)$
$\sigma_\mu \sim Cauchy(0,5)$
$\alpha \sim Cauchy(0,5)$
$\beta \sim Cauchy(0,5)$
σ_μ
μ_μ
$\mu_j \sim N(\mu_\mu, \sigma_\mu)$
$\sigma_j \sim \Gamma(\alpha, \beta)$
σ_j
μ_j
$V_{ij} \sim N(\mu_j, \sigma_j)$
$\beta_0 \cdots \beta_k \sim N(0,1000)$
$\mu_{2j} = \beta_1 + \cdots \beta_k Covariate_k + \alpha_1 \sigma_j + \alpha_2 \mu_j$
$\sigma_2 \sim Cauchy(0,5)$
σ_2
μ_{2j}
$Y_j \sim N(\mu_{2j}, \sigma_2)$

SIMULATION RESULTS

- 2 x 2 x 2 x 2 simulation study conducted[3] with a total of 16 distinct conditions varying the number of days (5, 14), the sample size (80, 250), the effect size (small, large), and IIV (low, high)
- Compared to using the ISD, the BVM produced
  - Unbiased estimates in most conditions, and even in worst cases (few repeated measures, low variability, and small sample size) produced less biased estimates than ISD
  - Good coverage (95% credible intervals included true value about 95% of the time)
  - Provides equal or more power than ISD

[3]Wiley, J. F., Bei, B., Trinder, J., & Manber, R. (2014). Variability as a Predictor: A Bayesian Variability Model for Small Samples and Few Repeated Measures. *arXiv preprint arXiv:1411.2961*.

SIMULATION RESULTS : PERCENTAGE BIAS

Average Relative Bias x 100 across Simulations

	Low Variability: $\Gamma(4, 1)$				High Variability: $\Gamma(1, .25)$			
	$N = 80$		$N = 250$		$N = 80$		$N = 250$	
	$k = 5$	$k = 14$	$k = 5$	$k = 14$	$k = 5$	$k = 14$	$k = 5$	$k = 14$
Small Effect								
ISDM	-33.32	-18.98	-35.89	-16.75	-12.54	-3.18	-11.48	-3.87
BVM	16.20	-2.92	1.76	-1.62	5.13	2.27	4.77	0.64
Large Effect								
ISDM	-34.51	-15.90	-35.64	-15.37	-13.72	-4.12	-13.74	-4.80
BVM	10.43	0.29	2.31	-0.11	3.57	1.74	2.18	0.54

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SIMULATION RESULTS : COVERAGE

Empirical Coverage of 95% Confidence Intervals

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	$N = 80$		$N = 250$		$N = 80$		$N = 250$	
	$k = 5$	$k = 14$	$k = 5$	$k = 14$	$k = 5$	$k = 14$	$k = 5$	$k = 14$
Small Effect								
ISDM	.91	.93	.71	.89	.94	.94	.93	.94
BVM	.96	.95	.95	.94	.95	.95	.96	.95
Large Effect								
ISDM	.48	.84	.09	.67	.83	.92	.70	.90
BVM	.94	.94	.95	.93	.95	.96	.96	.95

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USING THE BAYESIAN VARIABILITY MODEL

- `varian` is a free R package for variability analysis using Bayesian inference
- User friendly
  - a few lines of code runs most basic models
  - diagnostics to help assess results
- Open source
  - All of the code and methods are open and online so that any researcher can check, validate, even copy and extend the work.
- Download from: https://github.com/ElkhartGroup/varian

USING THE BAYESIAN VAR

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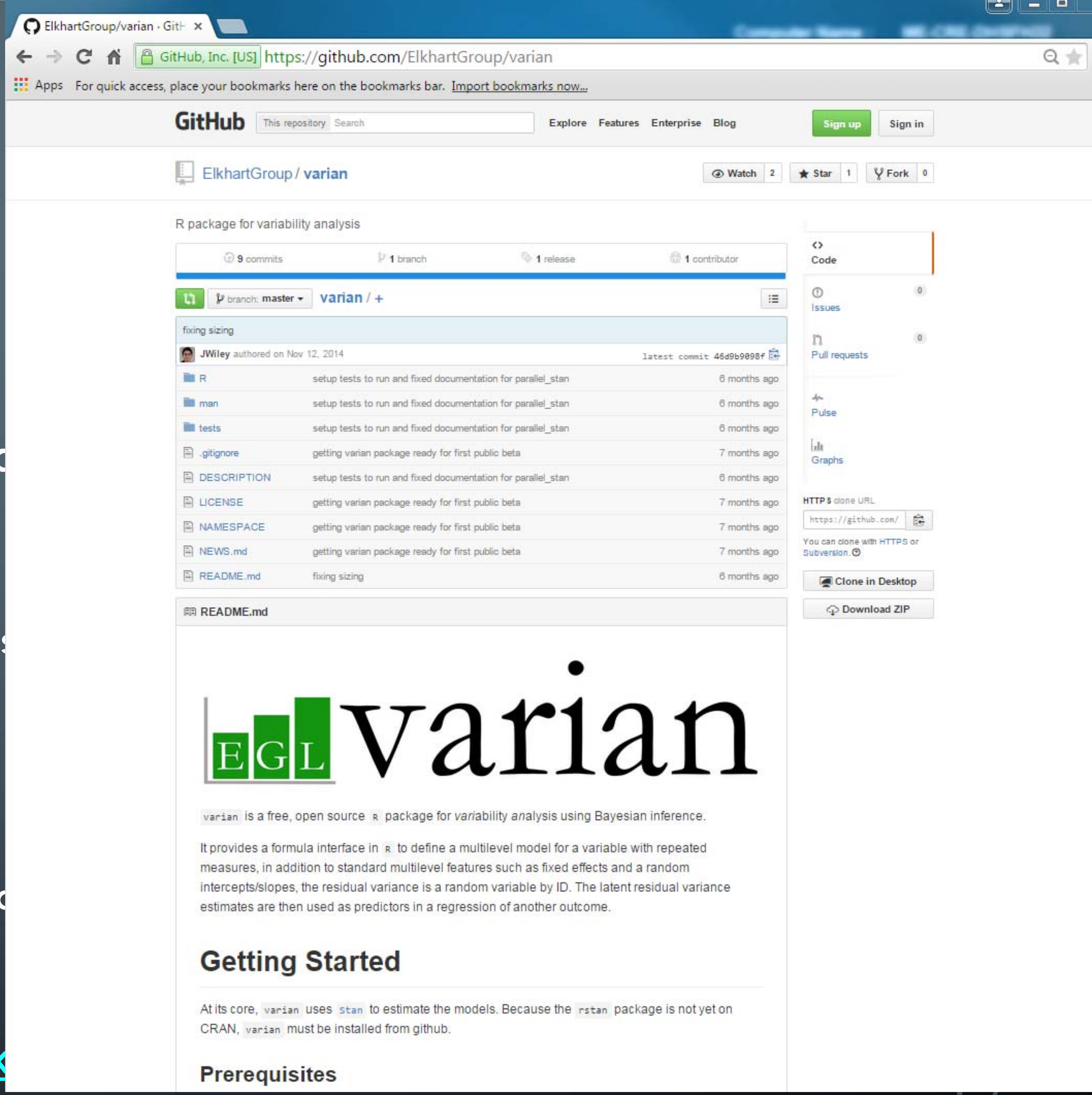

EMPIRICAL EXAMPLE

- Sample: 146 adolescents from the general community
- Daily actigraphy over 14 days of vacation (i.e., relatively unconstrained sleep
- Other questionnaires on: Subjective Sleep Quality, Negative Mood, Life Stress

[4]Bei, B., Wiley, J. F., Allen, N., Manber, R., & Trinder, J. See Wednesday Poster Board #154

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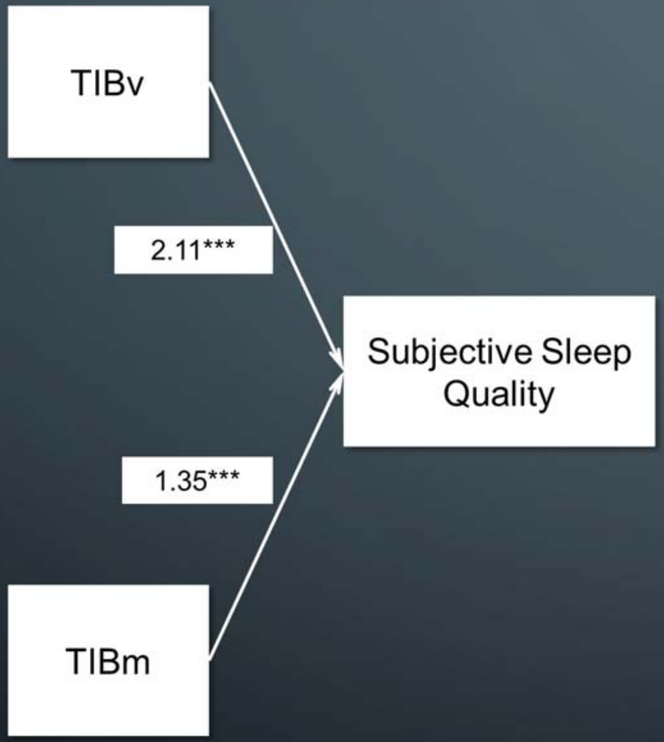

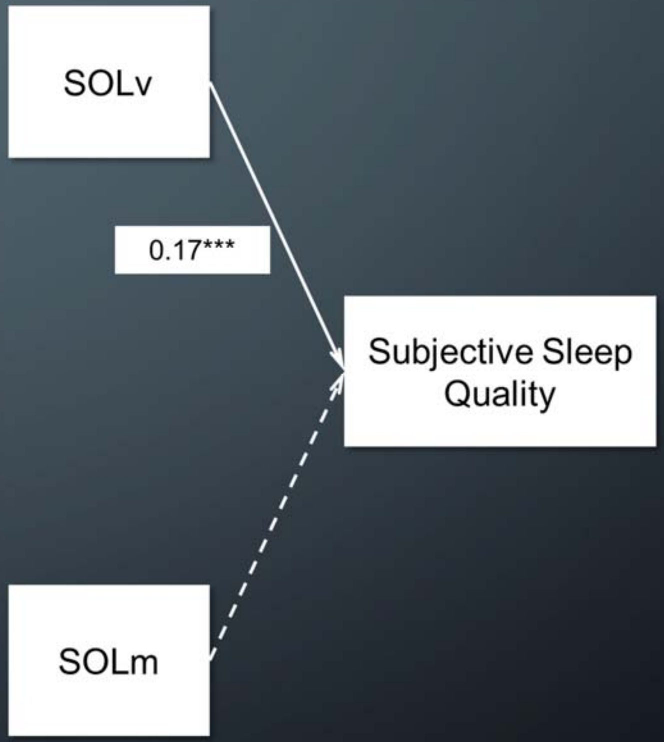

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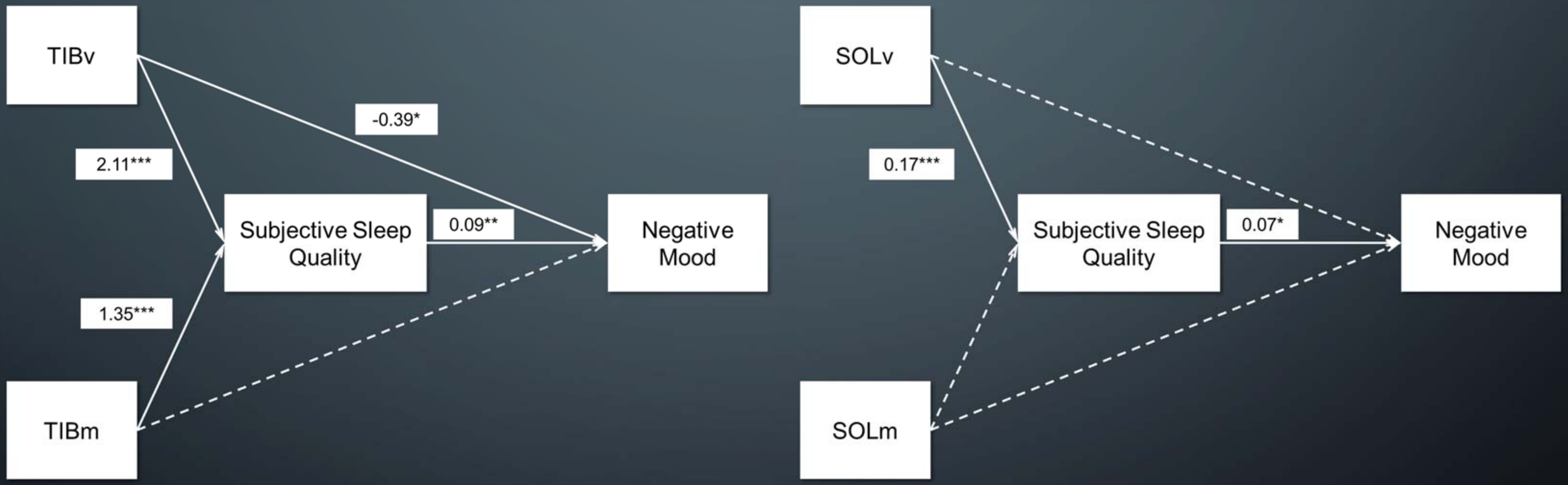

[4]Bei, B., Wiley, J. F., Allen, N., Manber, R., & Trinder, J. See Wednesday Poster Board #154

THANKS!

For more information

- Wiley, J. F., Bei, B., Trinder, J., & Manber, R. (2014). Variability as a Predictor: A Bayesian Variability Model for Small Samples and Few Repeated Measures. *arXiv preprint arXiv:1411.2961*.
- Software implementation: https://github.com/ElkhartGroup/varian

Questions about using the BVM to study variability in your data?

- Email/Call: josh@elkhartgroup.com / +1.260.673.5518