Is timing everything? The effects of measurement timing on the performance of nonlinear longitudinal models

—

Sebastian Sciarra

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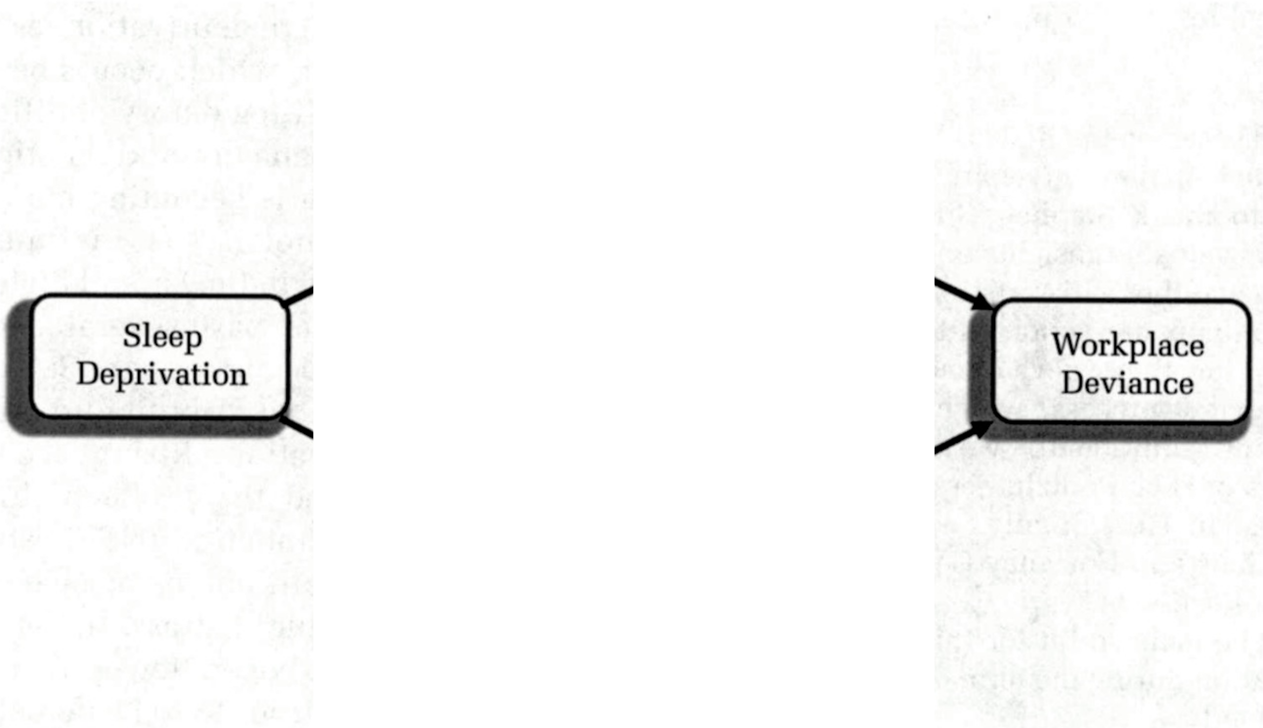
Model of workplace deviance

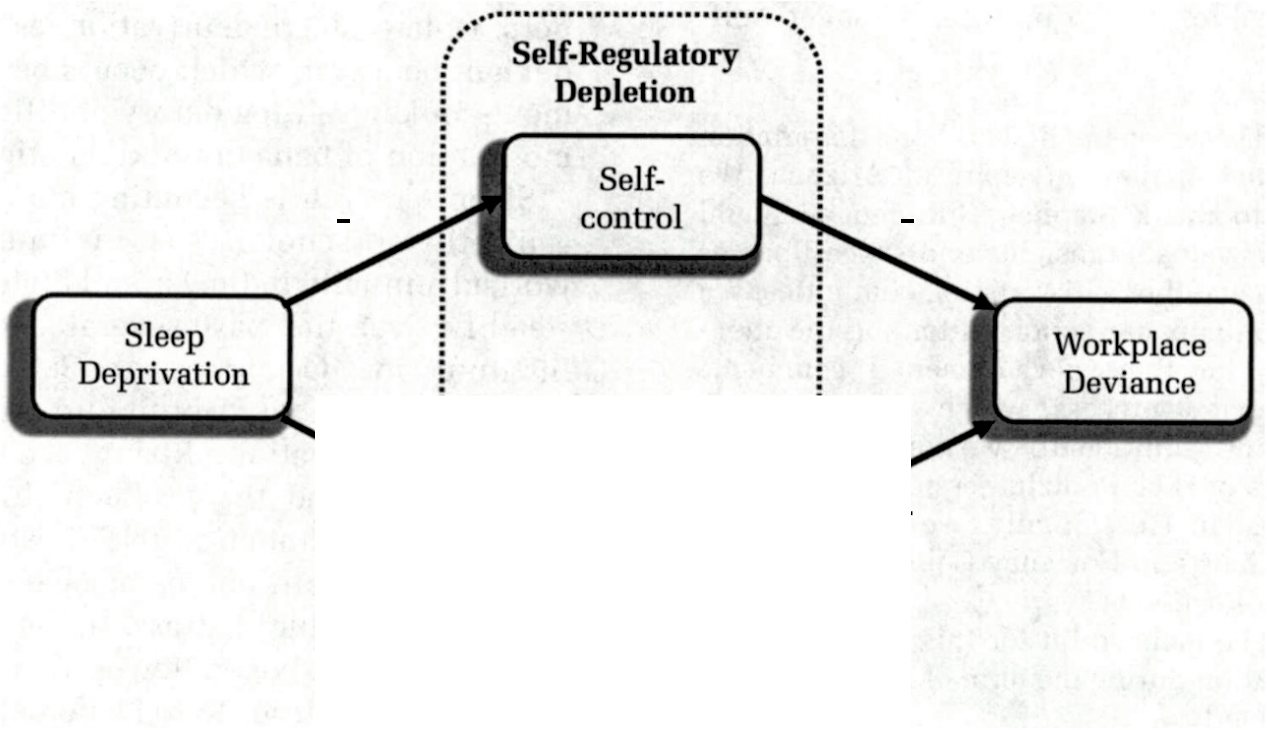
Christian & Ellis (2011)

Model of workplace deviance



Christian & Ellis (2011)

Model of workplace deviance



Christian & Ellis (2011)

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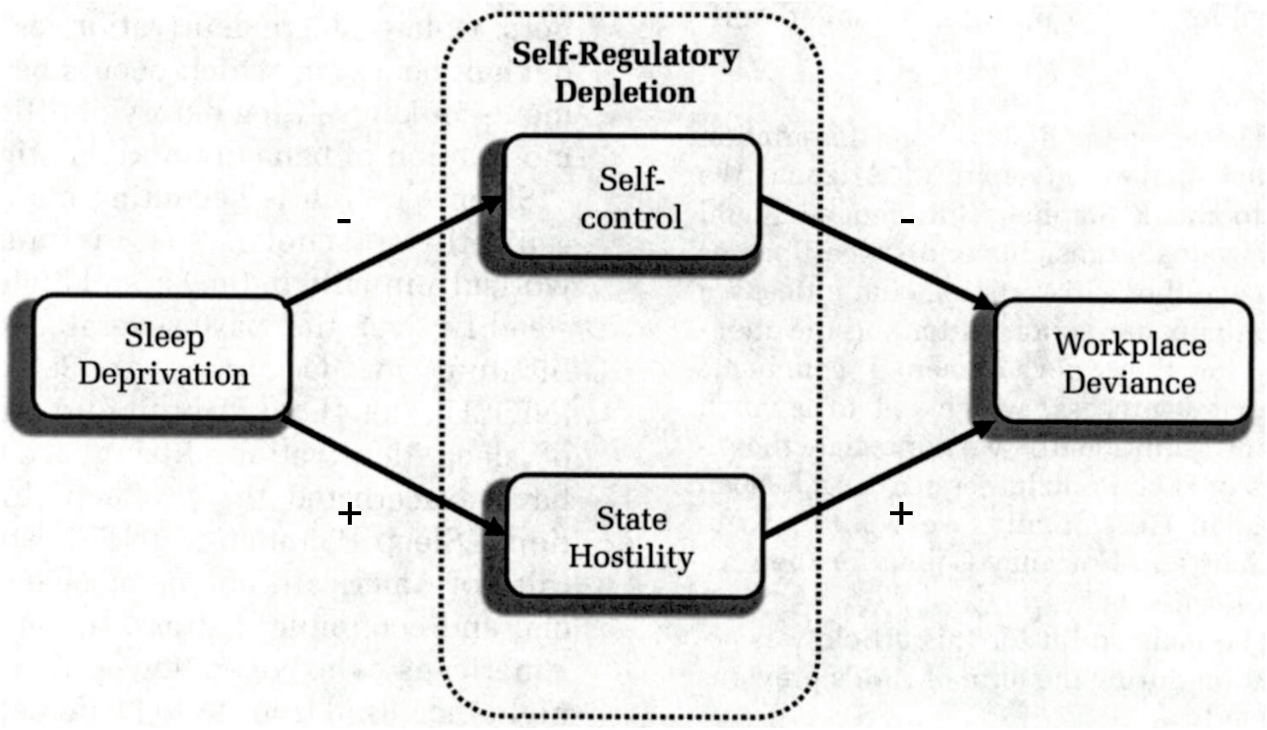
Model of workplace deviance



Christian & Ellis (2011)

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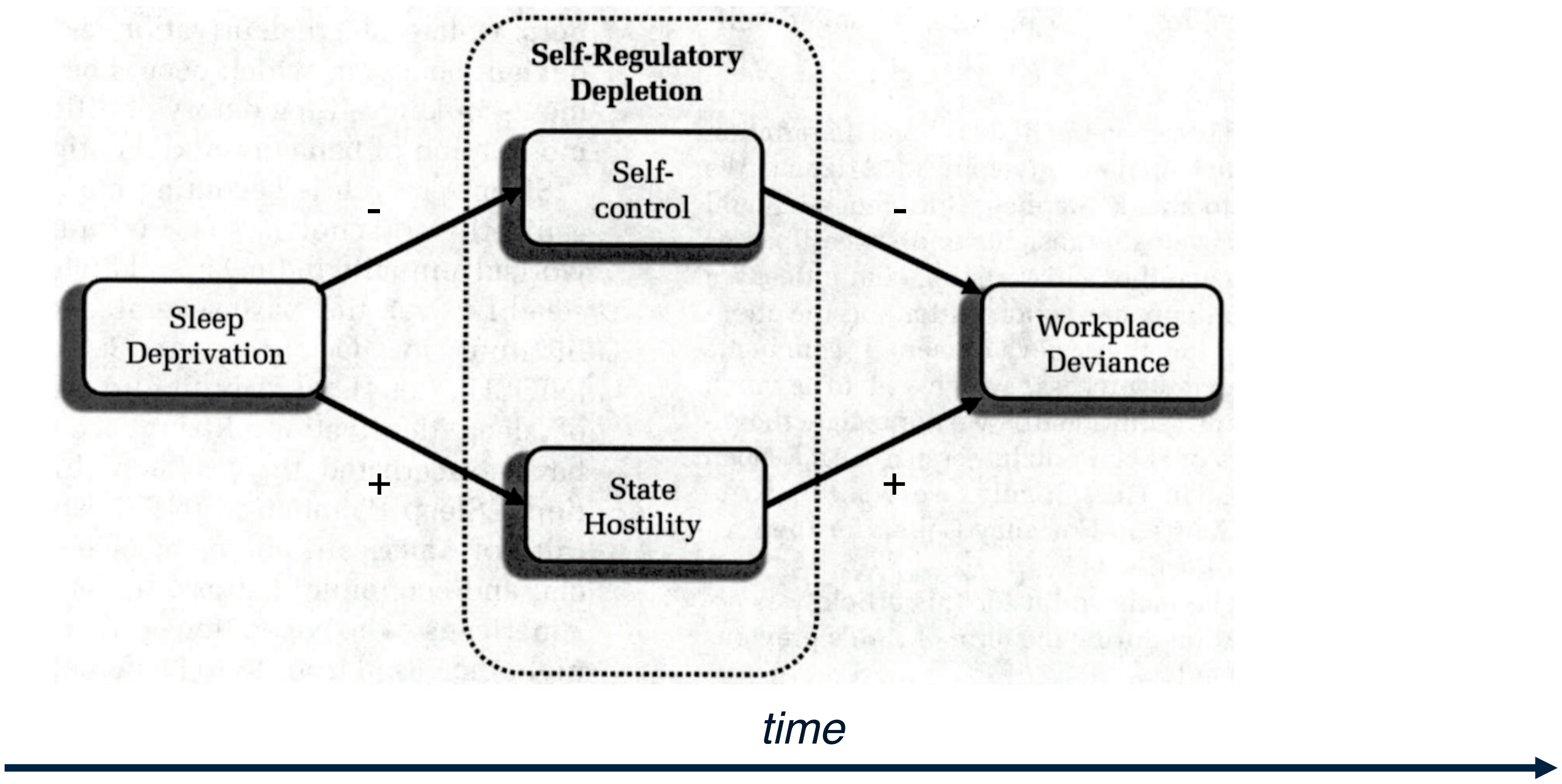
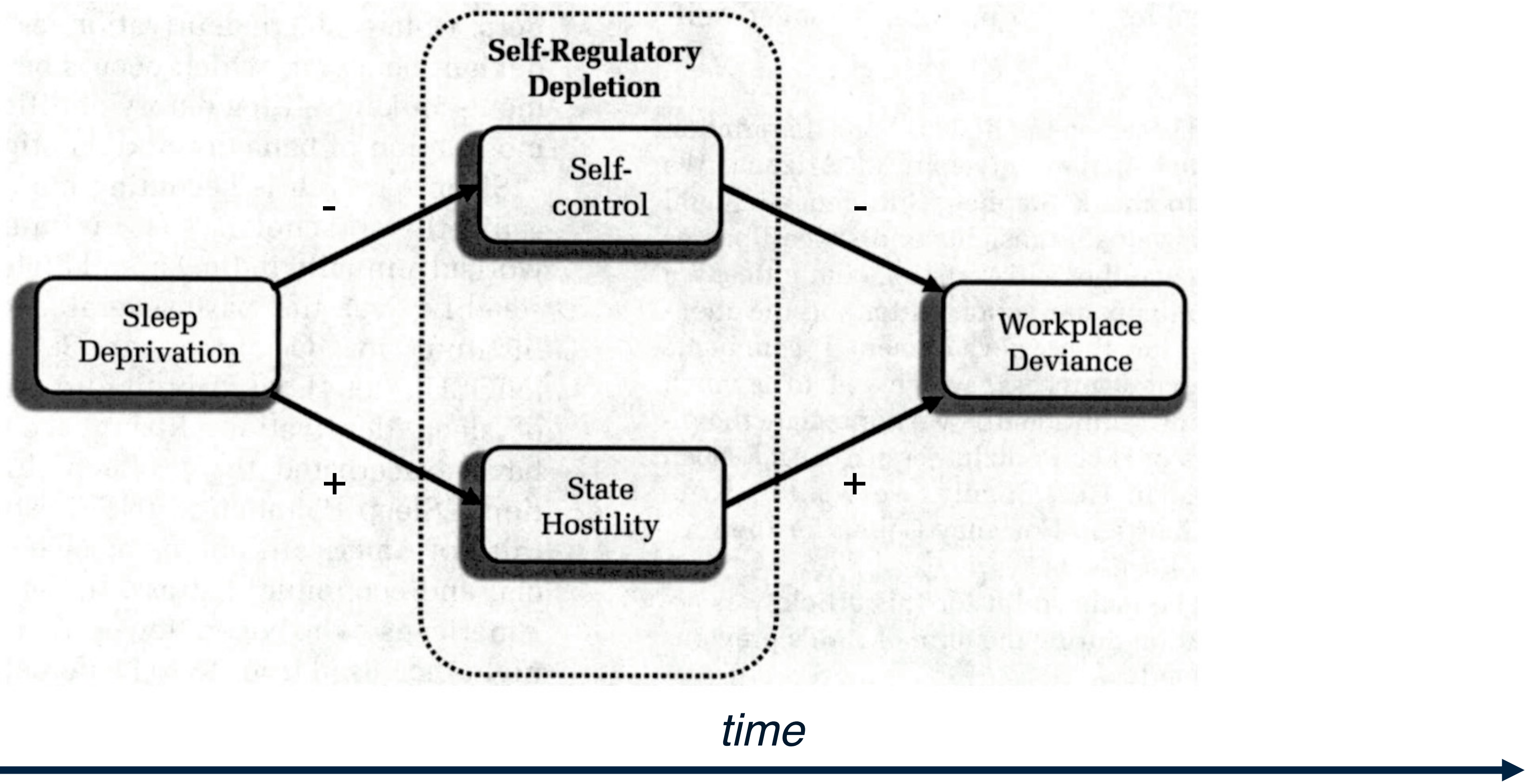
Model of workplace deviance



Christian & Ellis (2011)

Time is integral to understanding psychological processes

Model of workplace deviance



Christian & Ellis (2011)

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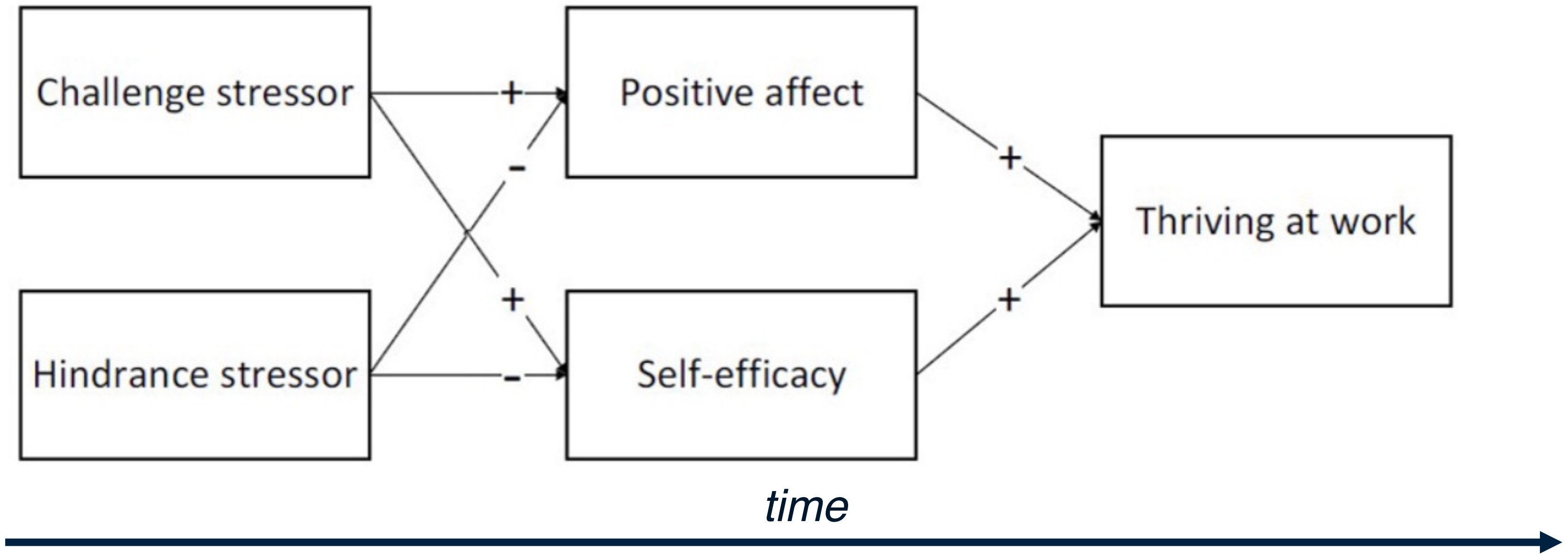
Time is integral to understanding psychological processes

Model of thriving at work



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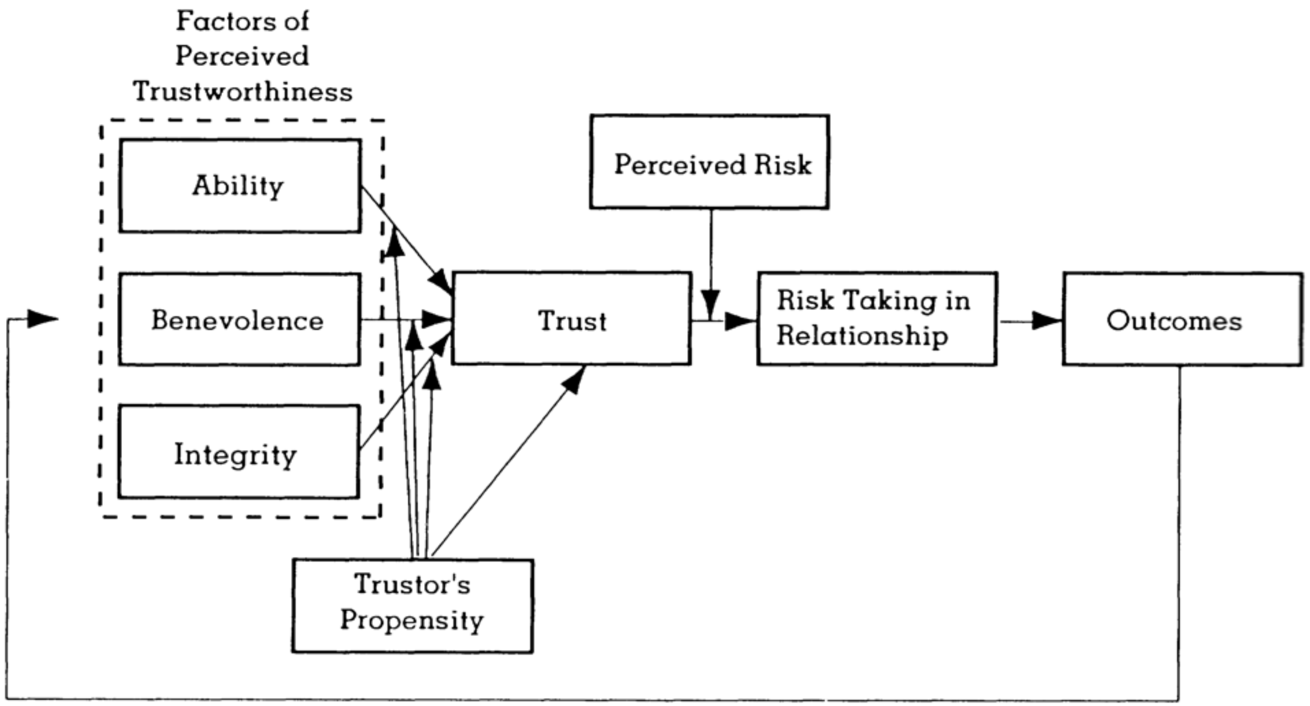
Yang & Li (2021)

Time is integral to understanding psychological processes

Model of organizational trust

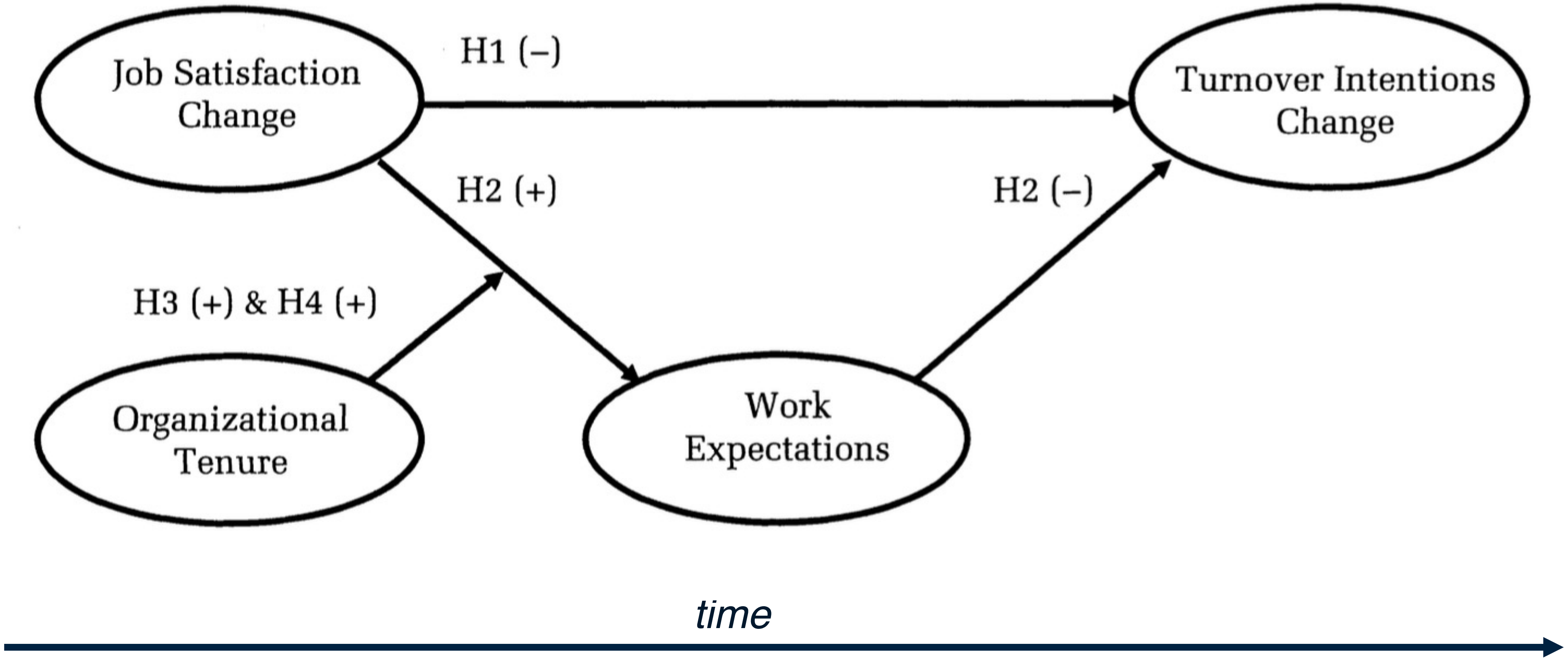


time

Mayer et al. (1995)

Time is integral to understanding psychological processes

Model of turnover intentions



Chen et al. (2011)

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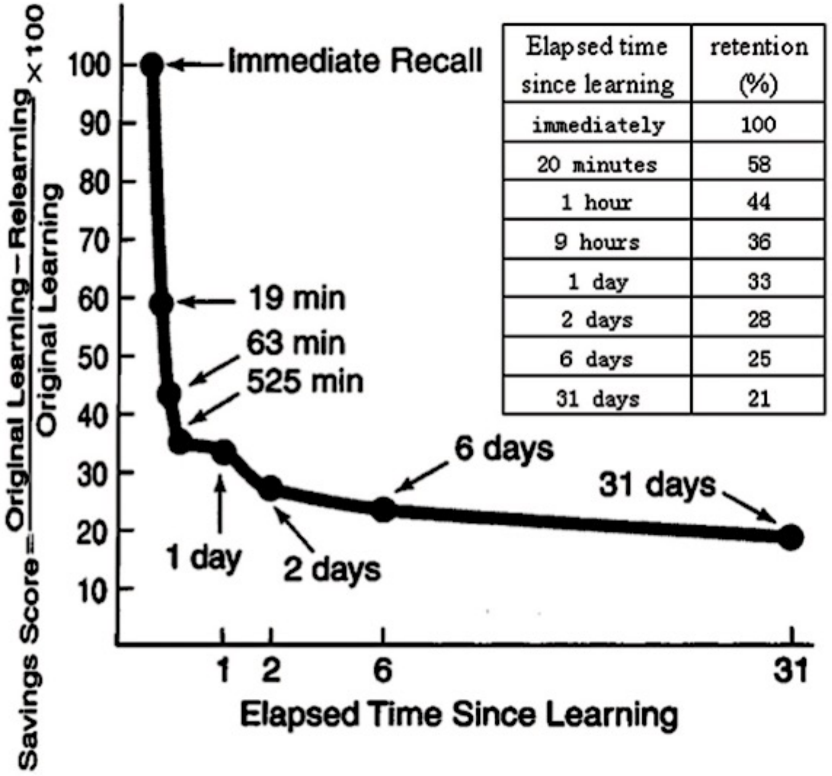
Change over time is likely to be nonlinear

Change over time is likely to be nonlinear

Forgetting curve



Li (2017)

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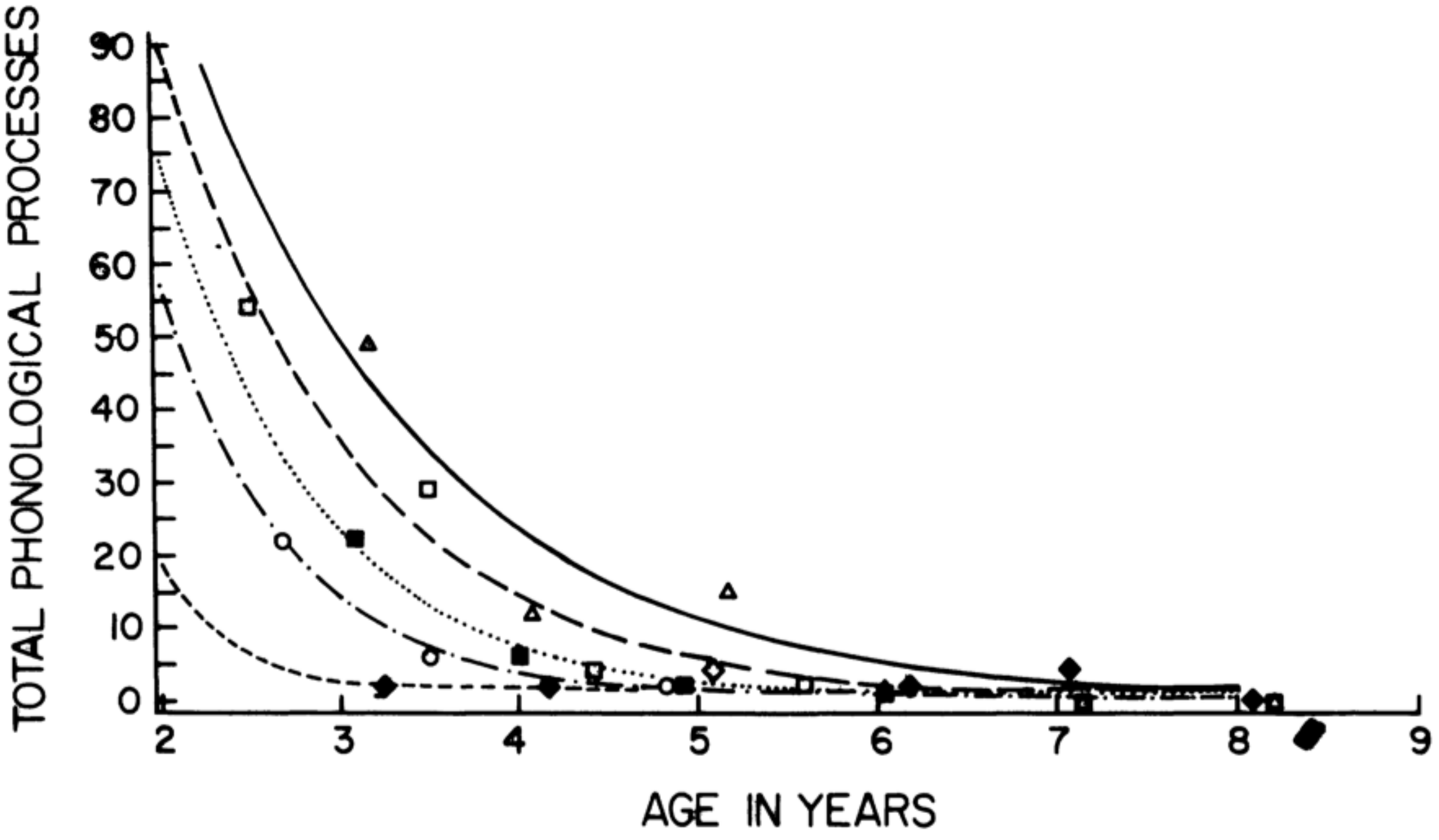
Change over time is likely to be nonlinear

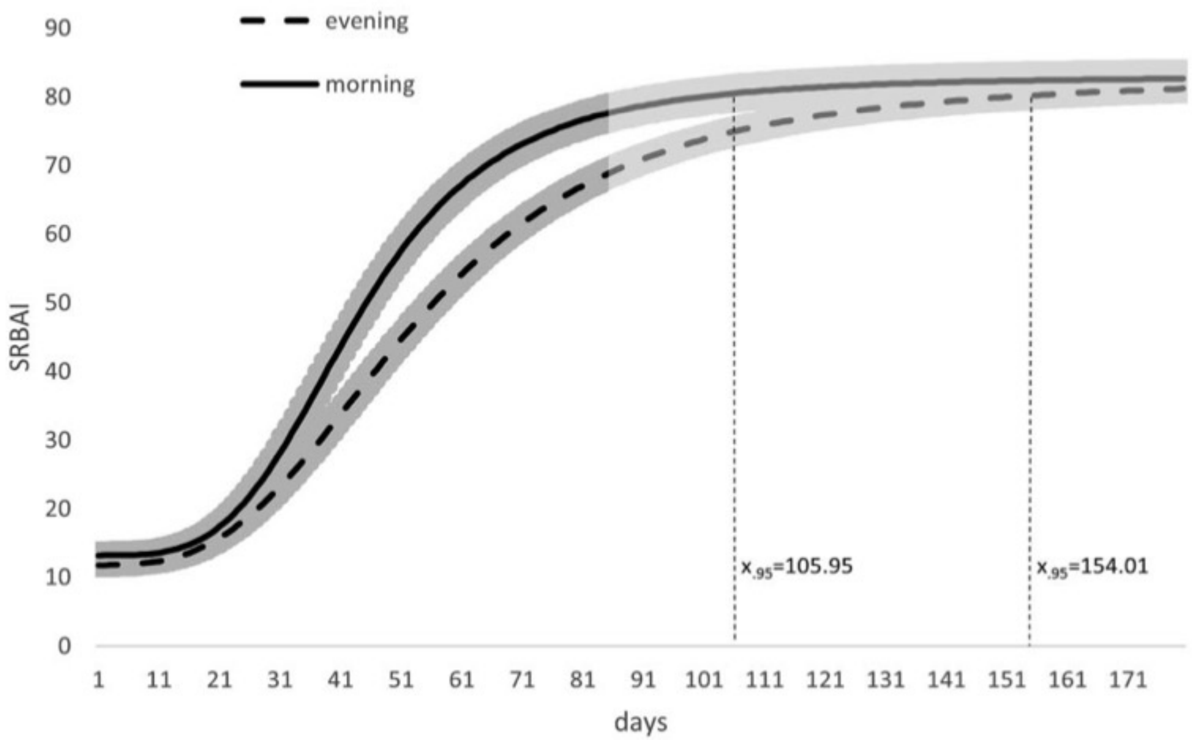
Number of speech errors throughout child development



Burchinal & Appelbaum (1991)

Change over time is likely to be nonlinear

Development of habits



Fournier et al. (2017)

Experiment 1

Question 1: Does placing measurements near periods of change increase model performance?

Question 2: How to space measurements when the nature of change is unknown?

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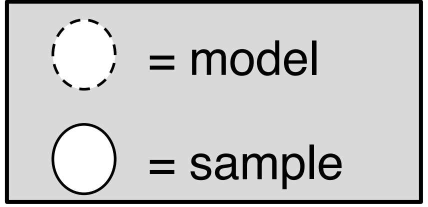
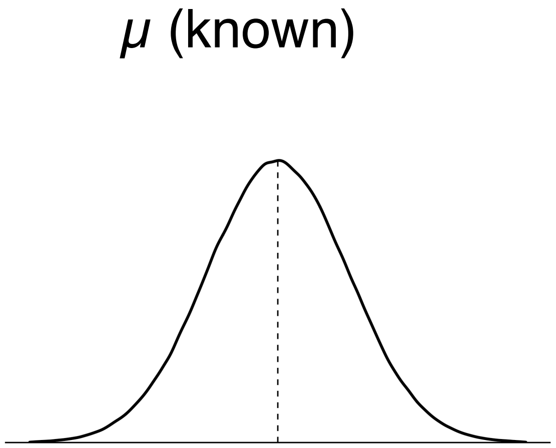
The Monte Carlo method



1. Population definition



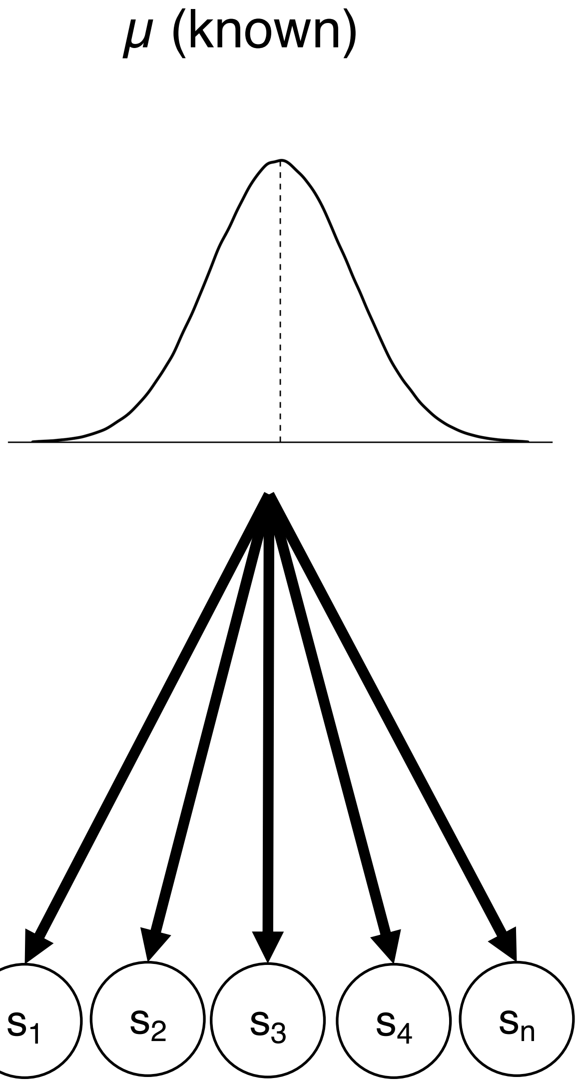
The Monte Carlo method

$\bigcirc$ = model

$\bigcirc$ = sample

1. Population definition

2. Sample generation



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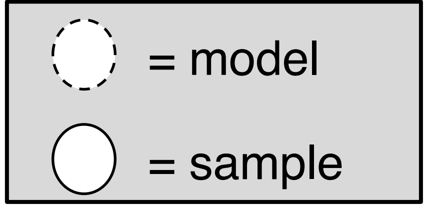
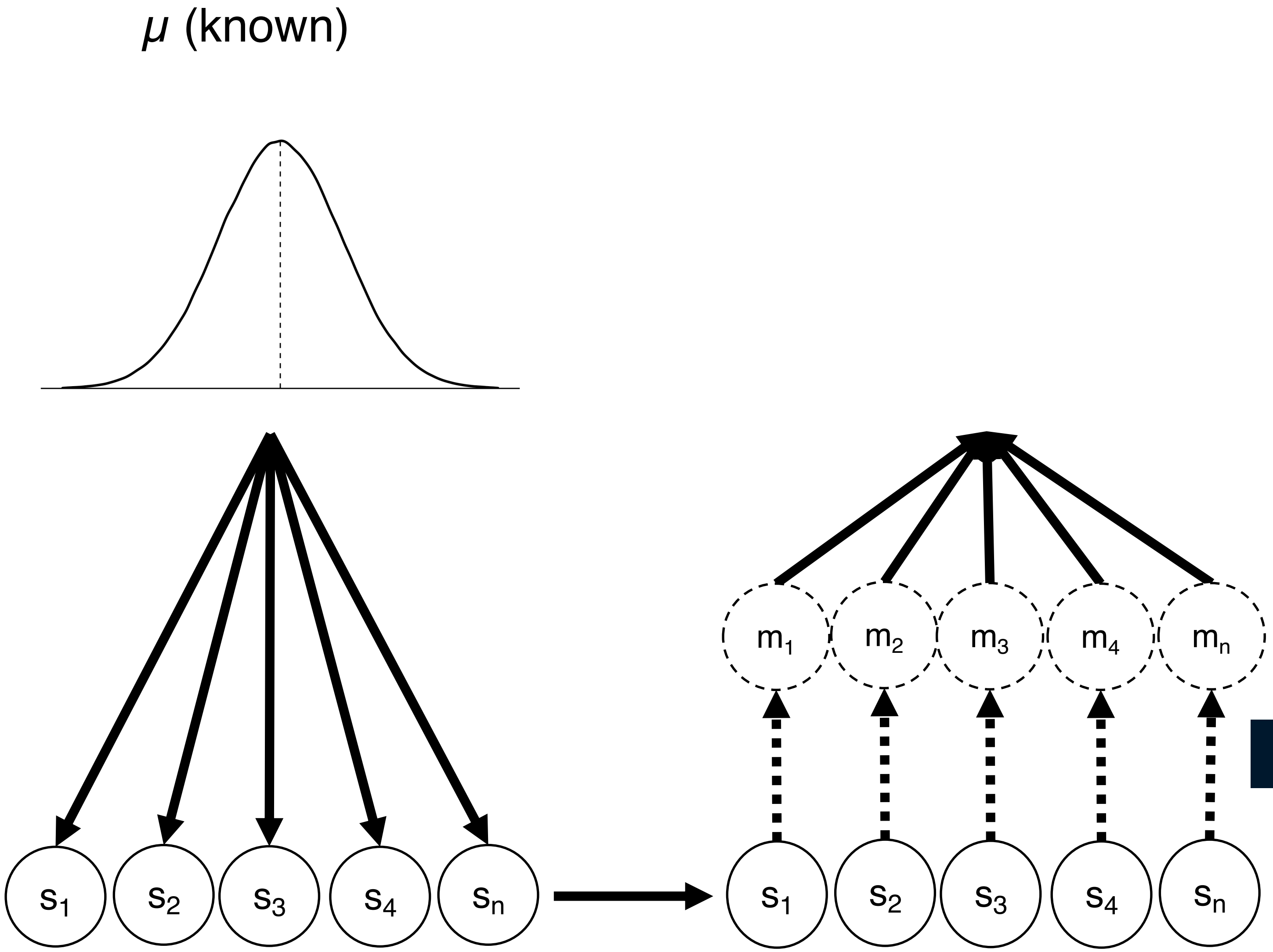
The Monte Carlo method



1. Population definition

2. Sample generation

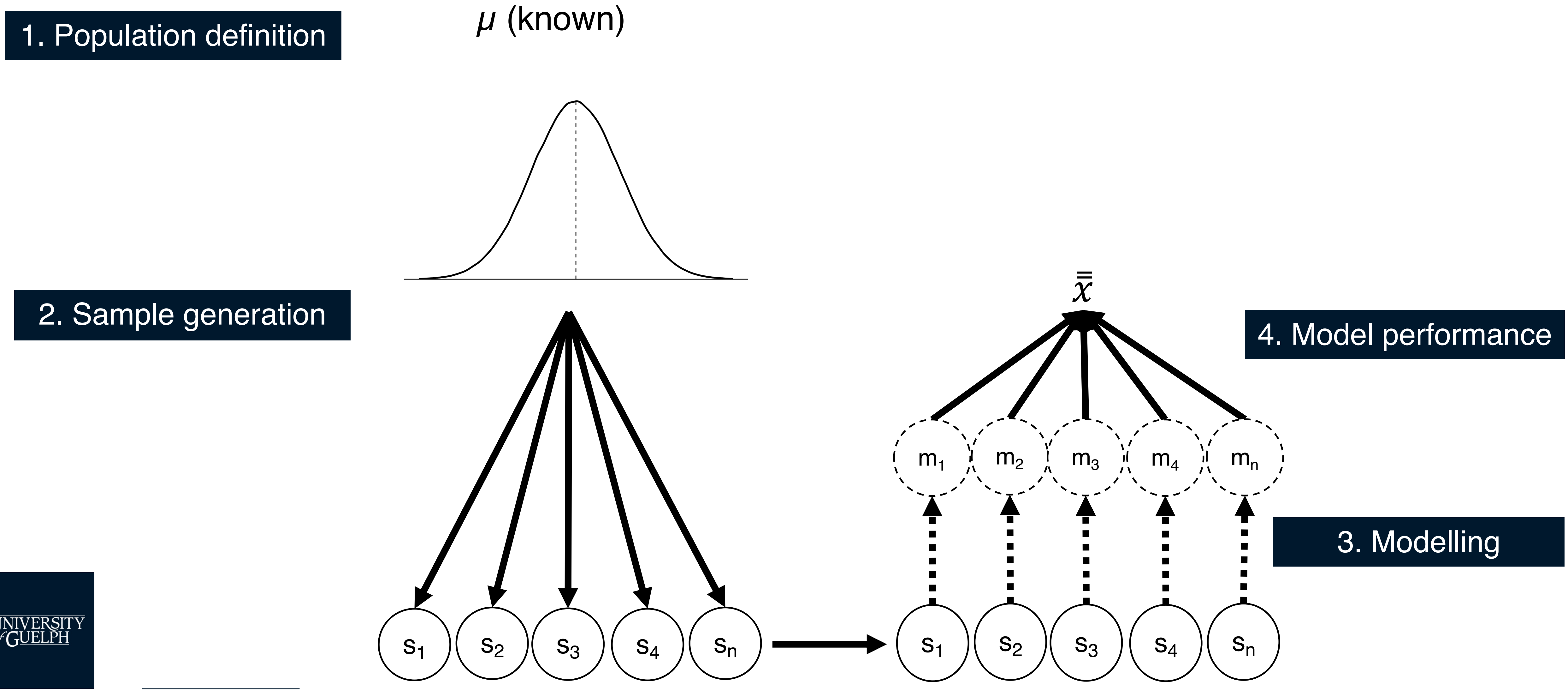
3. Modelling



The Monte Carlo method

= model

= sample



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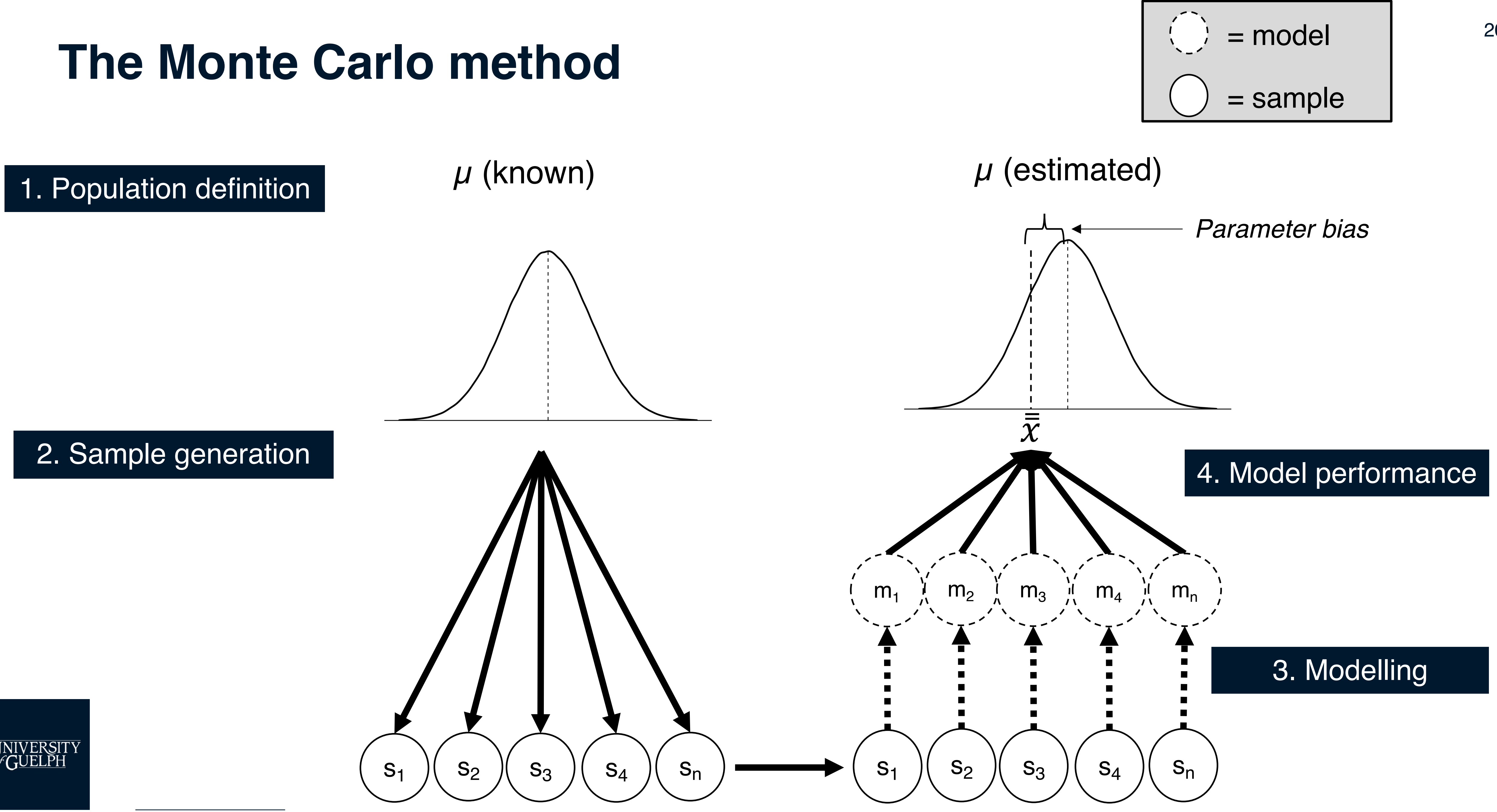
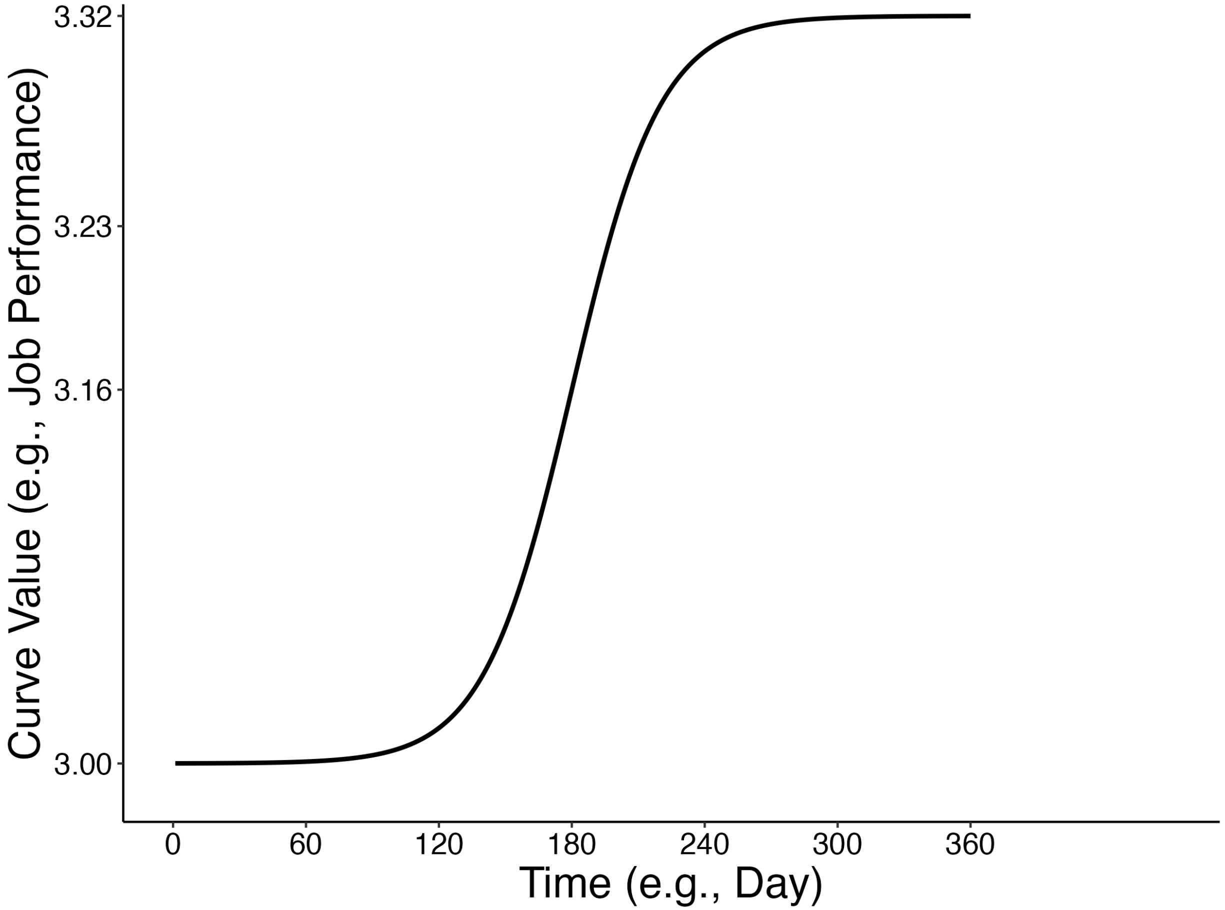
The Monte Carlo method



The Monte Carlo method: Population definition



Lawrence et al. (2001)

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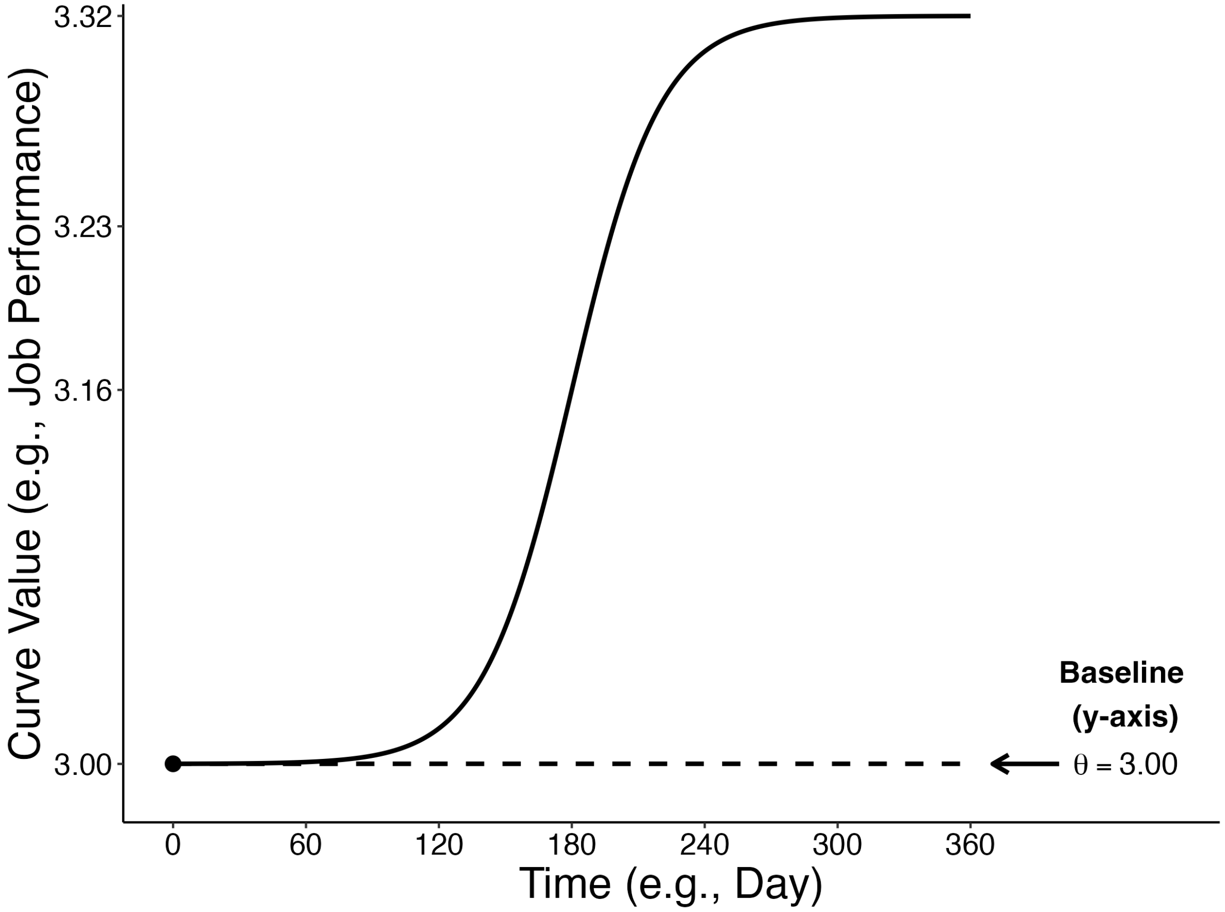
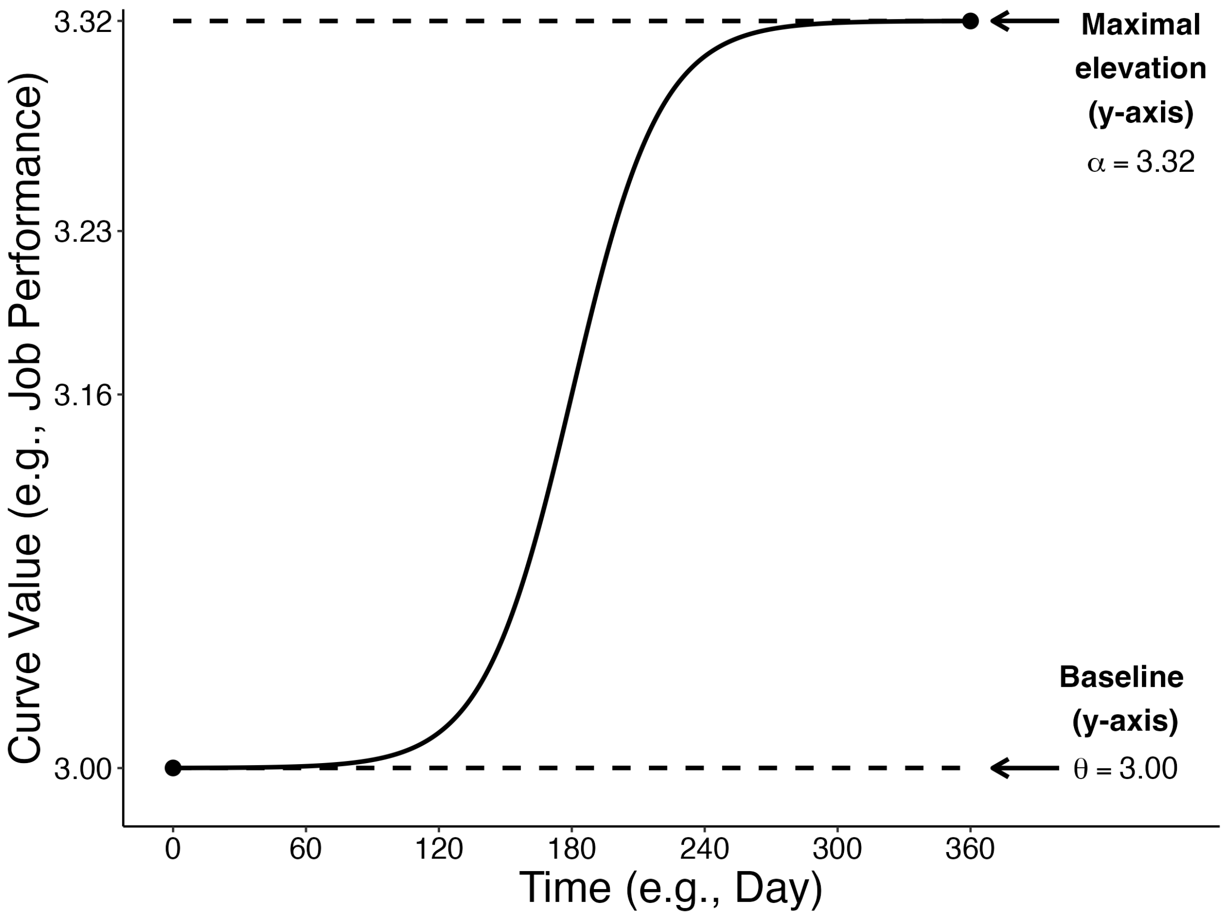
The Monte Carlo method: Population definition



1. Baseline (θ) = 3.00

The Monte Carlo method: Population definition



1. Baseline (θ) = 3.00
2. Maximal elevation (α) = 3.32

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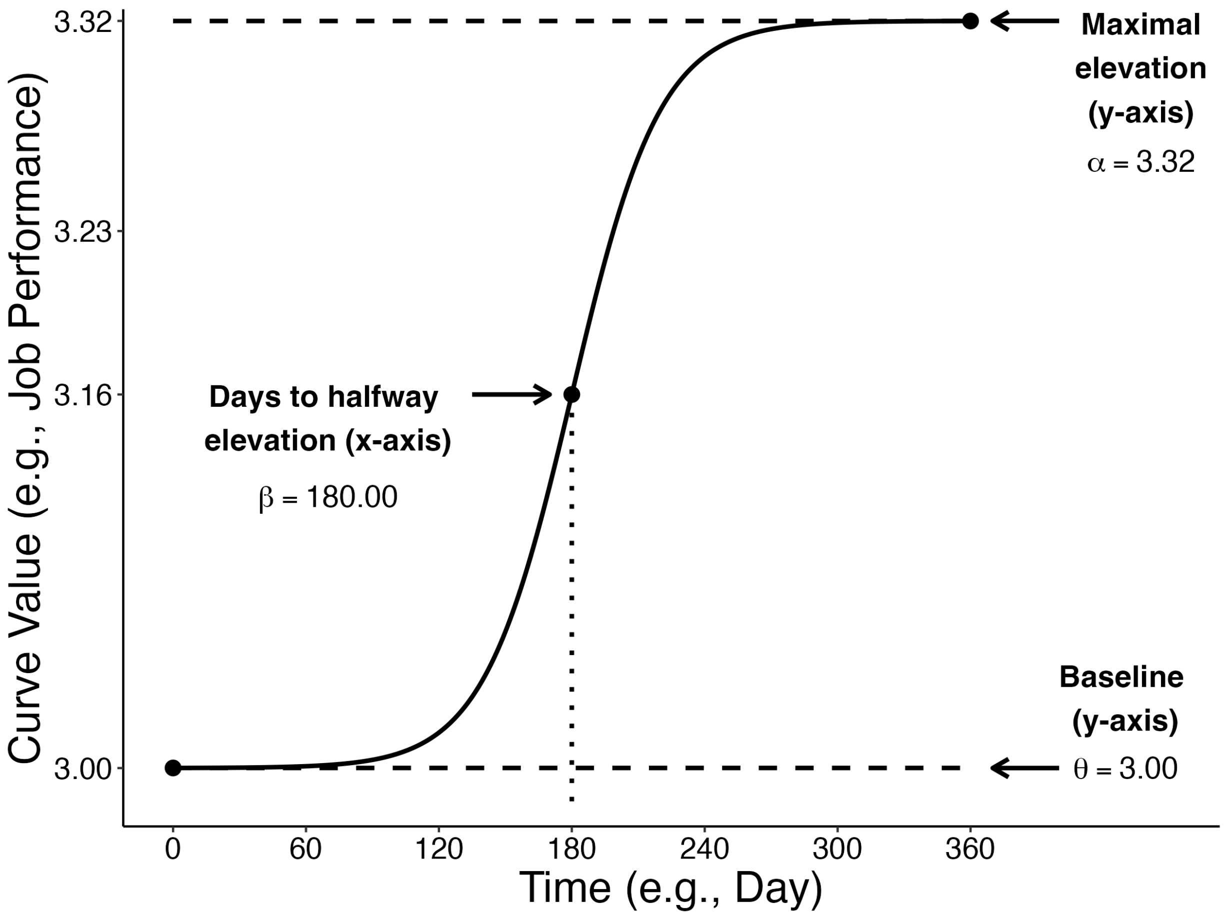
The Monte Carlo method: Population definition



1. Baseline (θ) = 3.00
2. Maximal elevation (α) = 3.32
3. Days to halfway elevation (β)= 180.00

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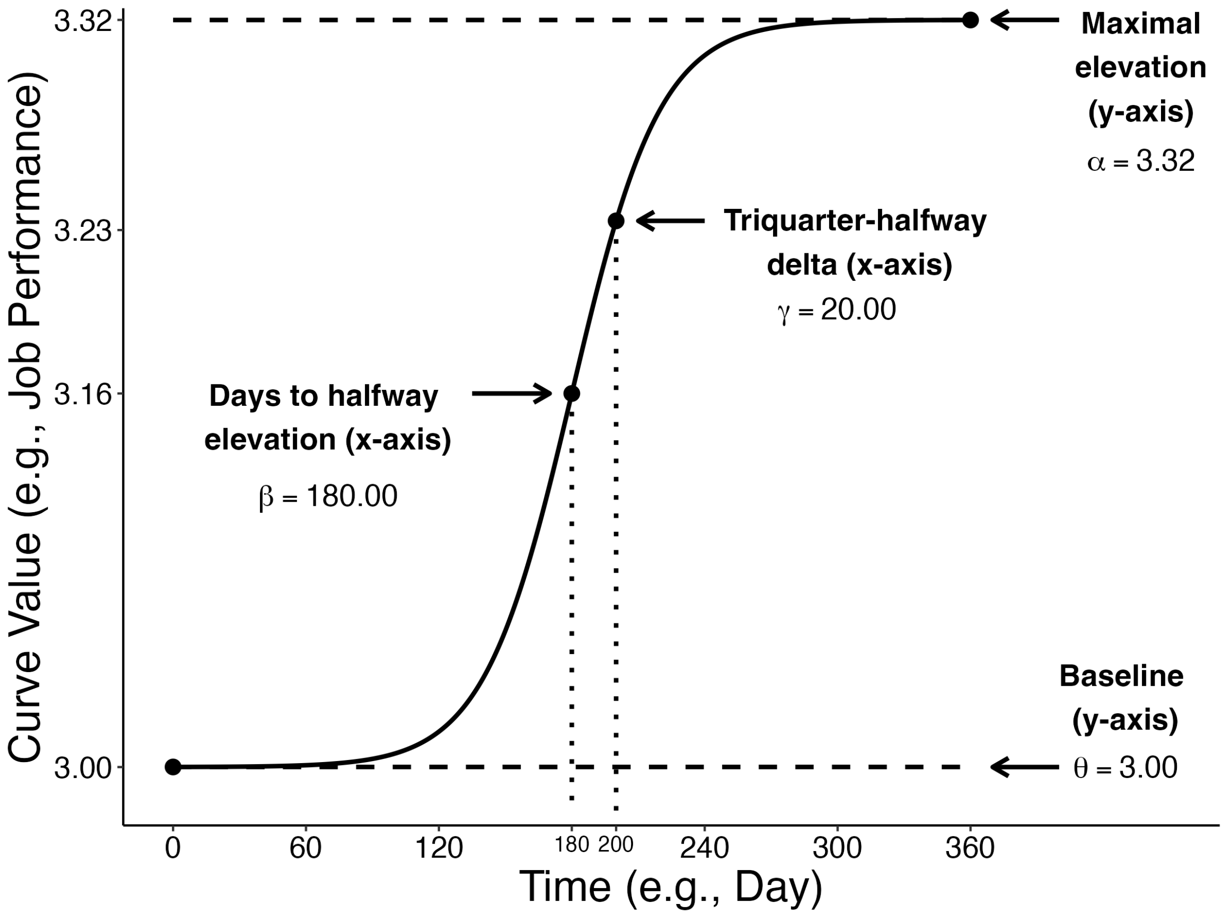
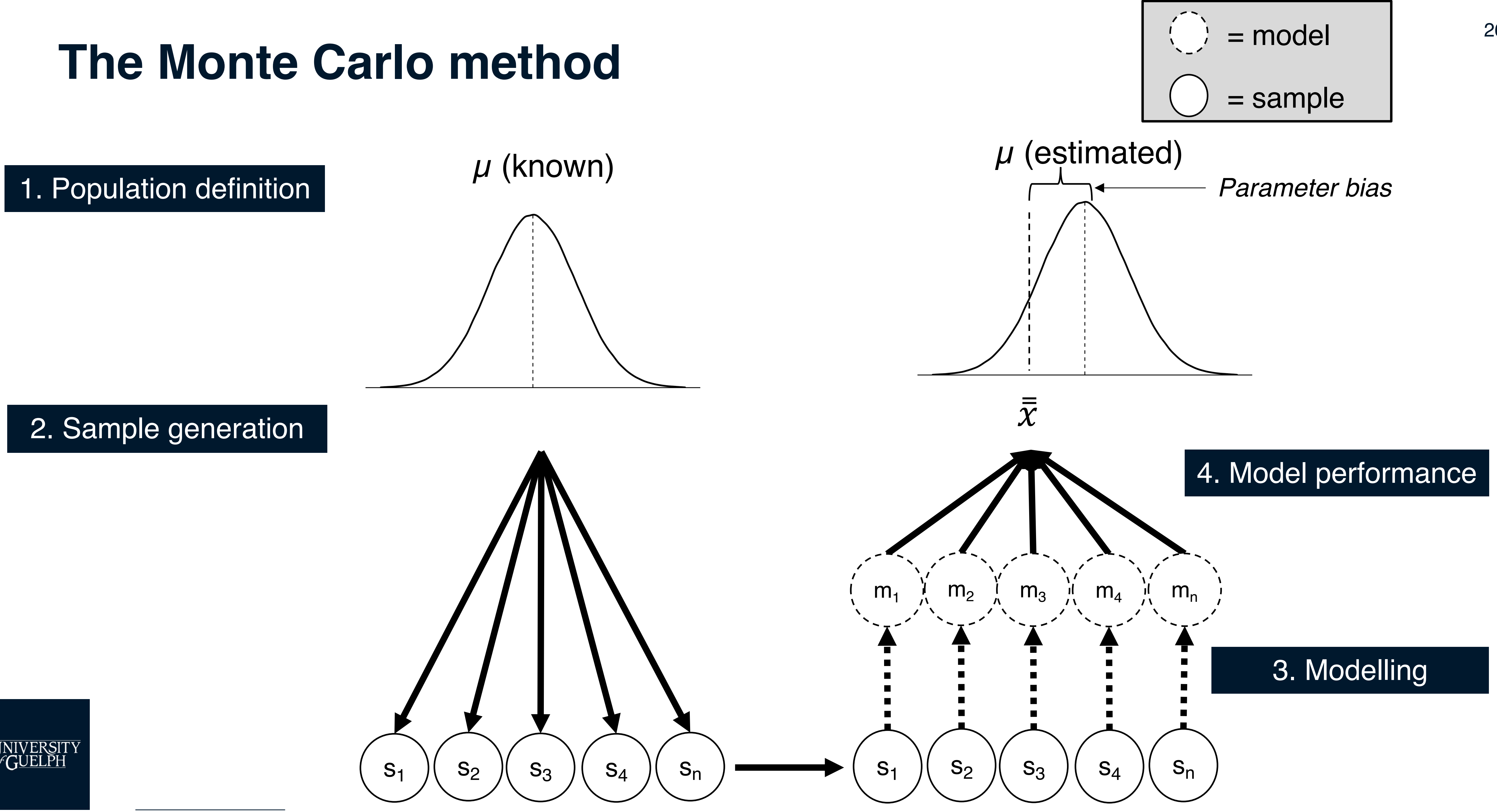
The Monte Carlo method: Population definition

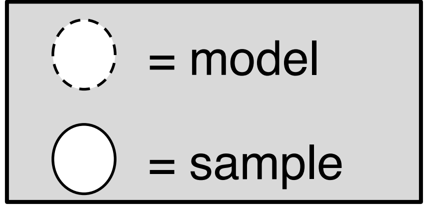


1. Baseline (θ) = 3.00
2. Maximal elevation (α) = 3.32
3. Days to halfway elevation (β)= 180.00
4. Triquarter-halfway delta (γ) = 20.00

The Monte Carlo method



The Monte Carlo method

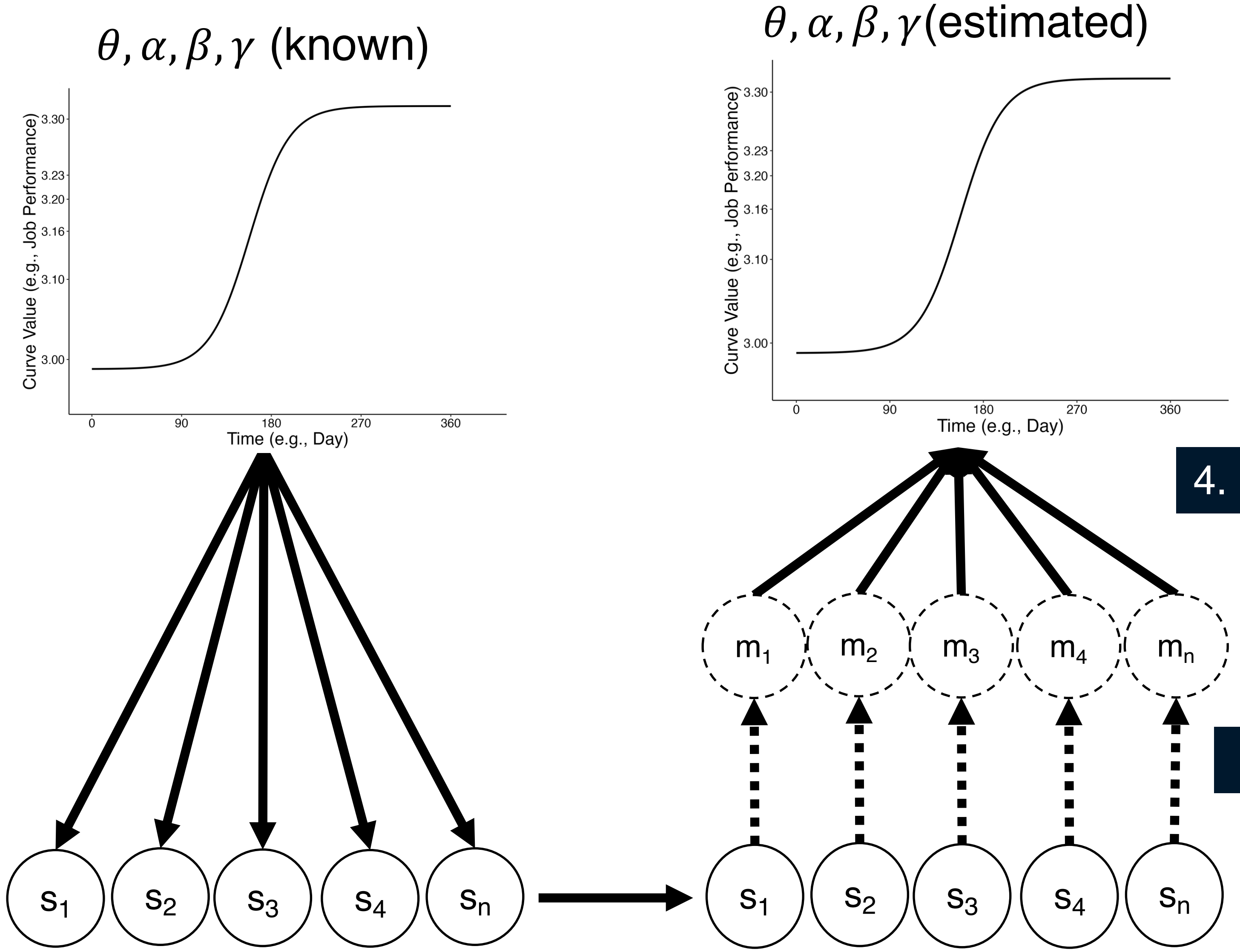


1. Population definition

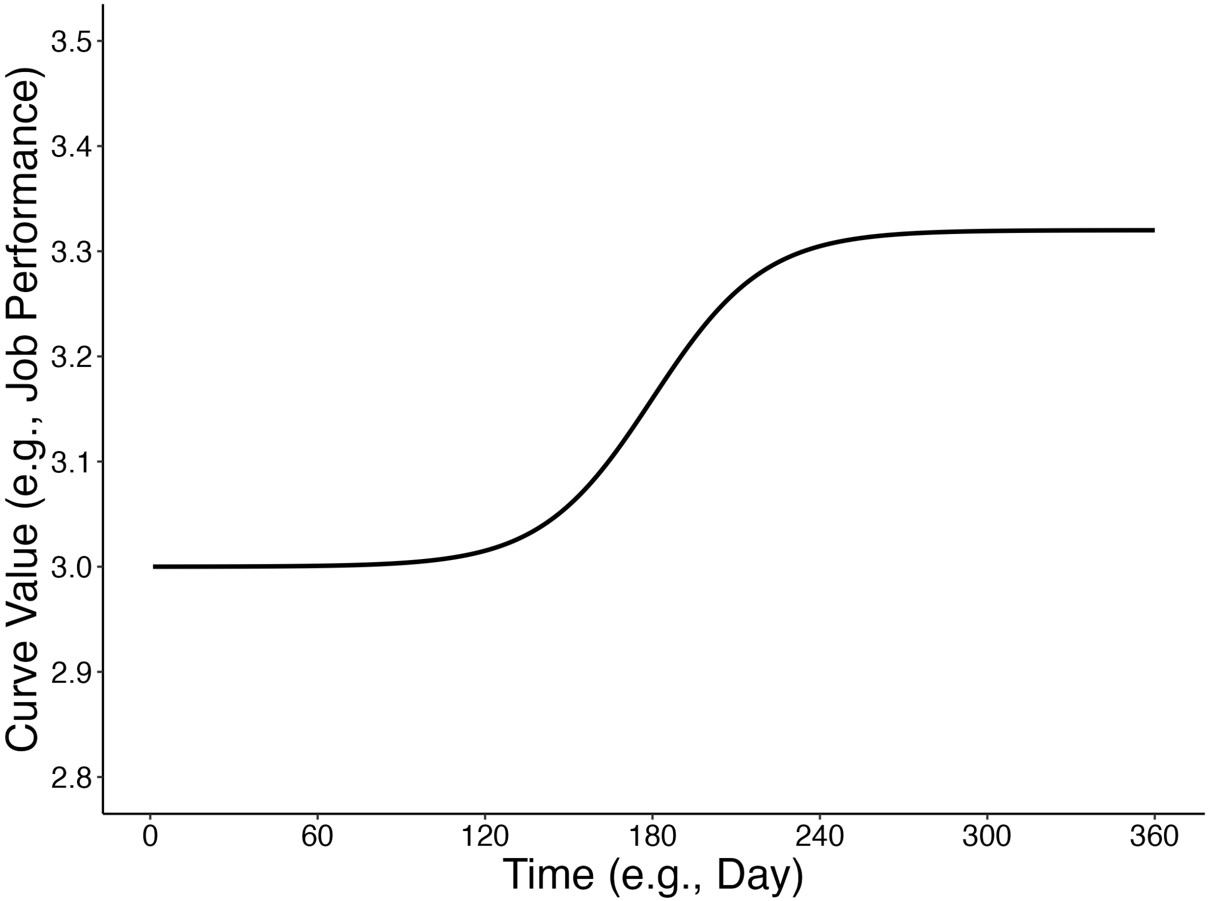
2. Sample generation

3. Modelling

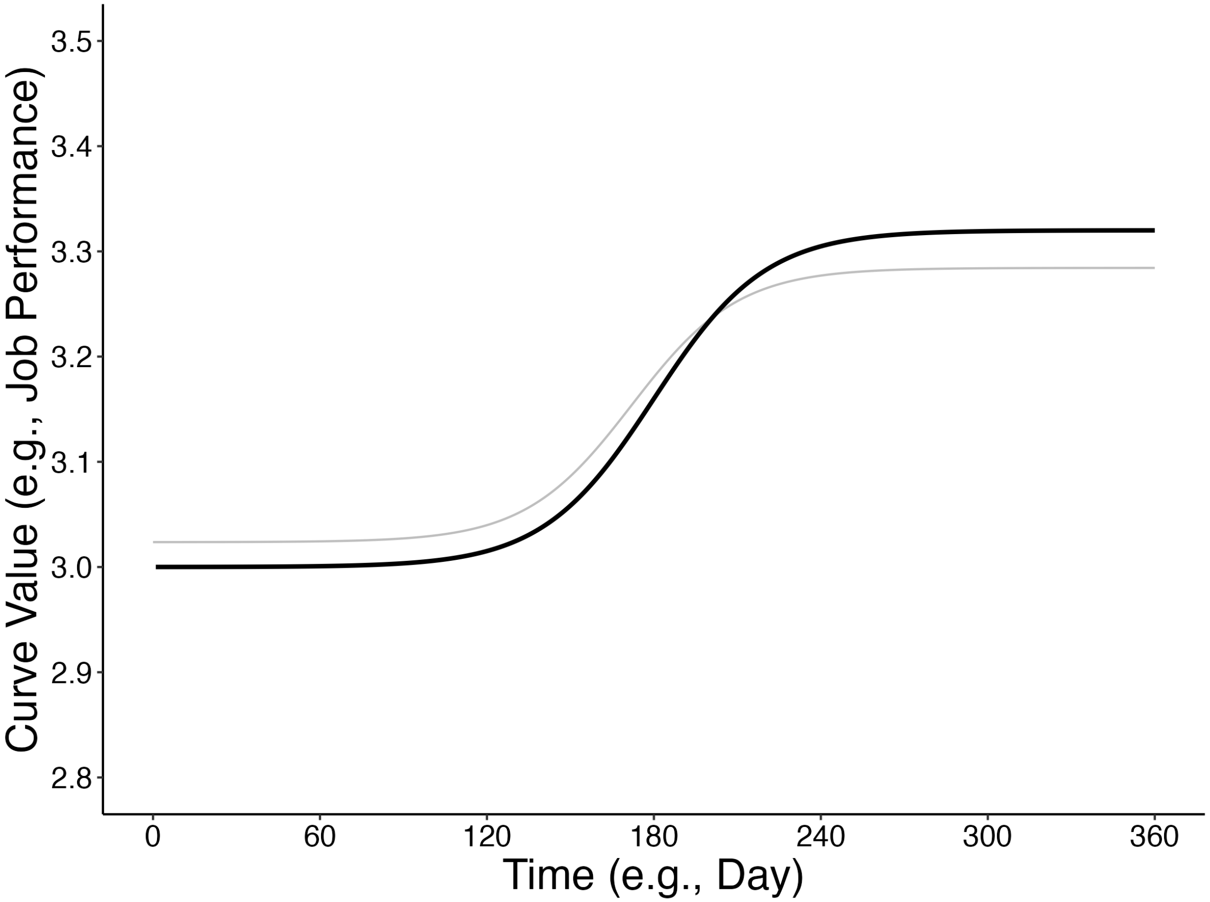
4. Model performance



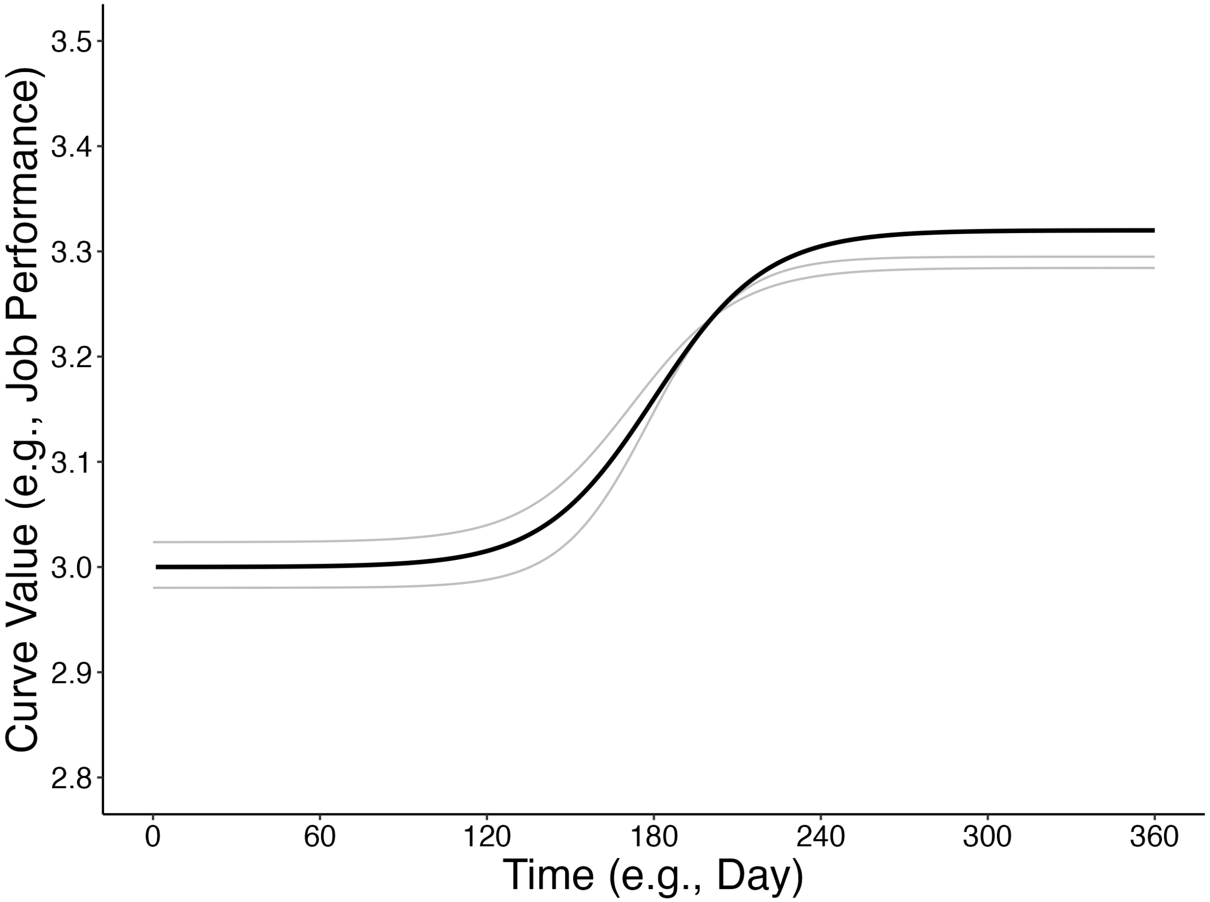
The Monte Carlo method: Population definition



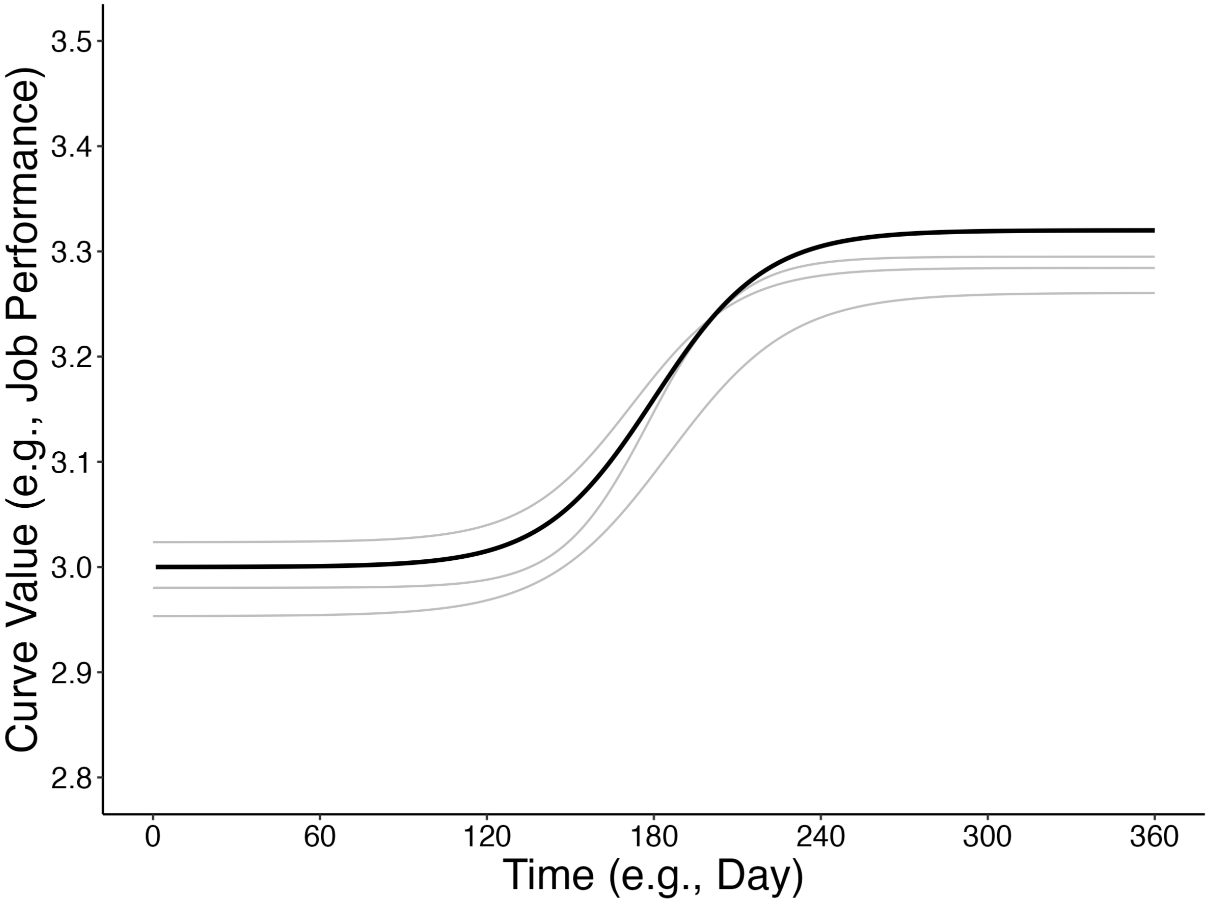
The Monte Carlo method: Population definition



The Monte Carlo method: Population definition



The Monte Carlo method: Population definition



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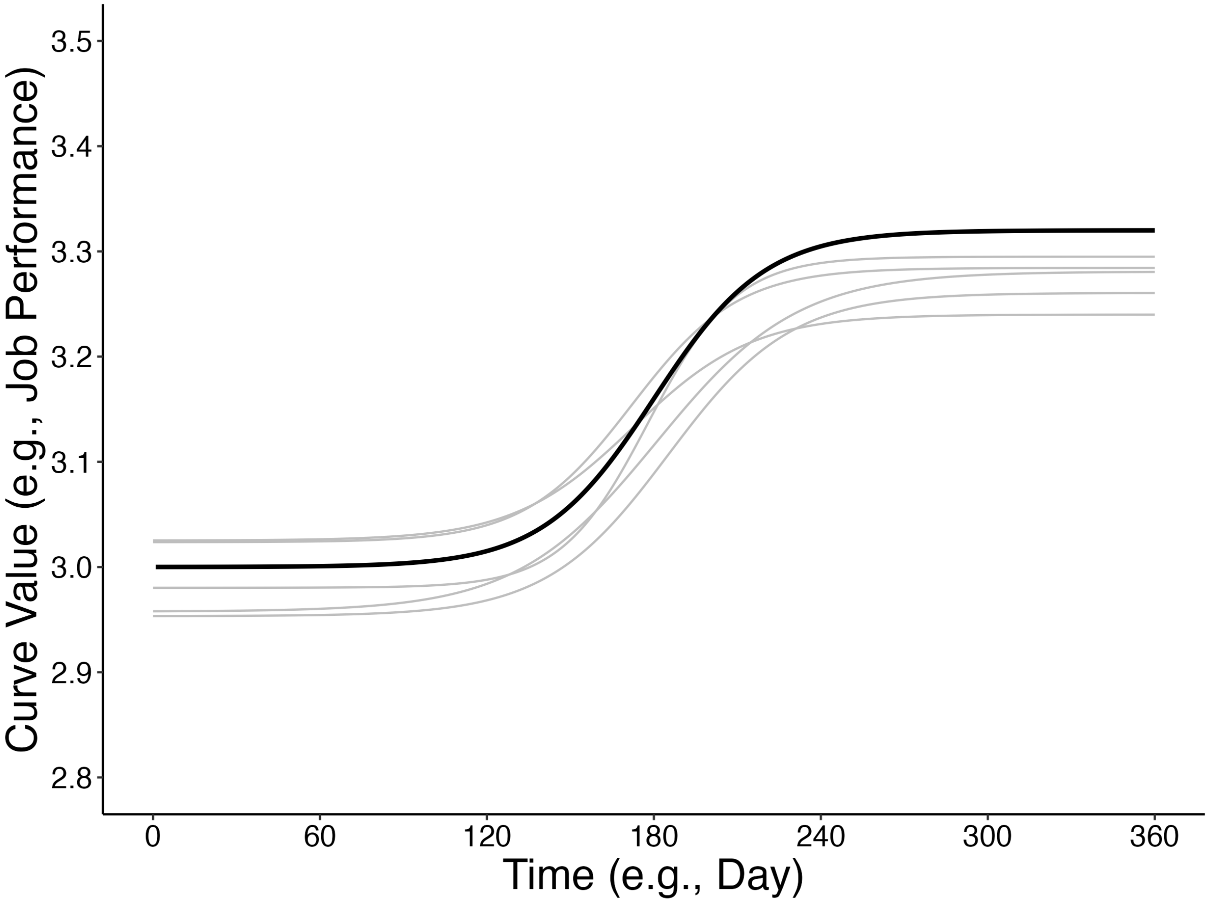
The Monte Carlo method: Population definition



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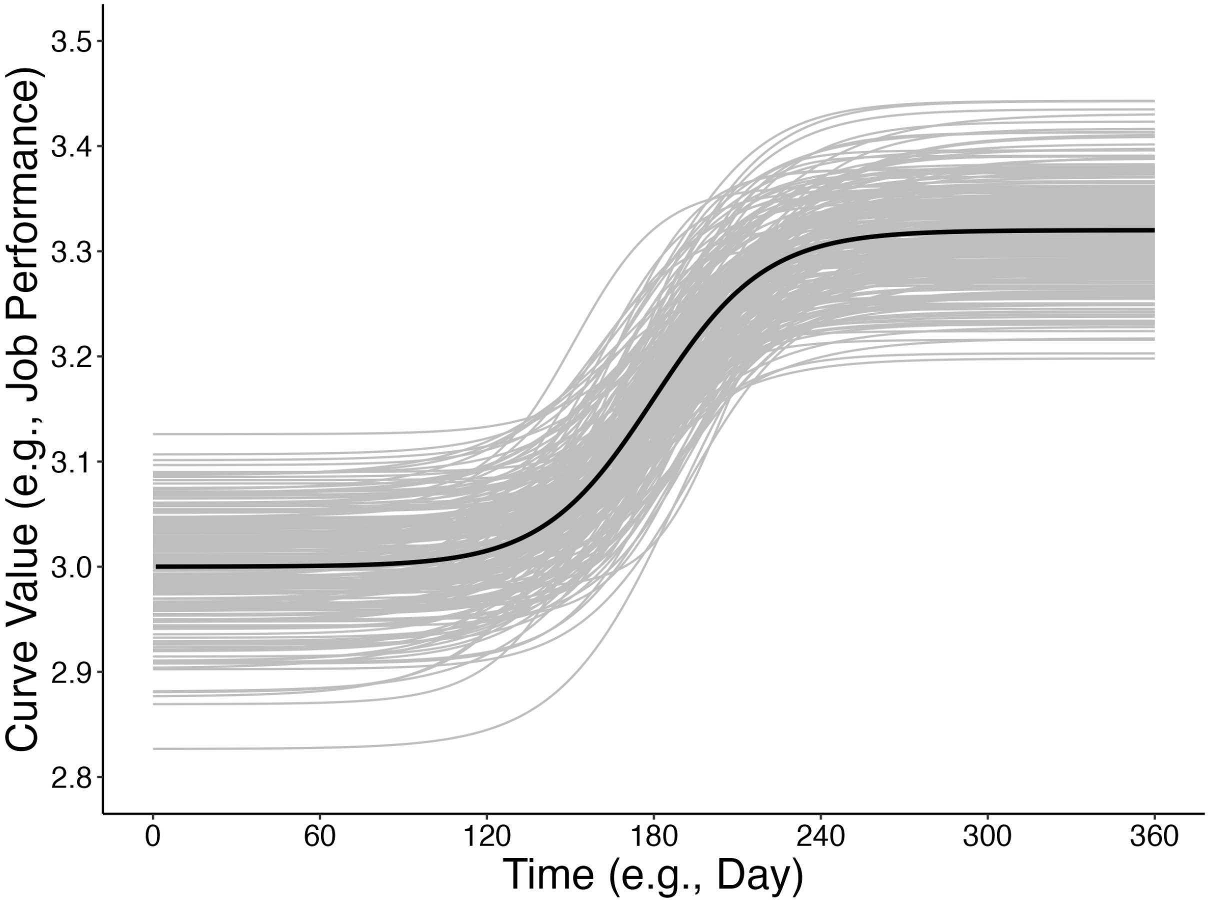
The Monte Carlo method: Population definition



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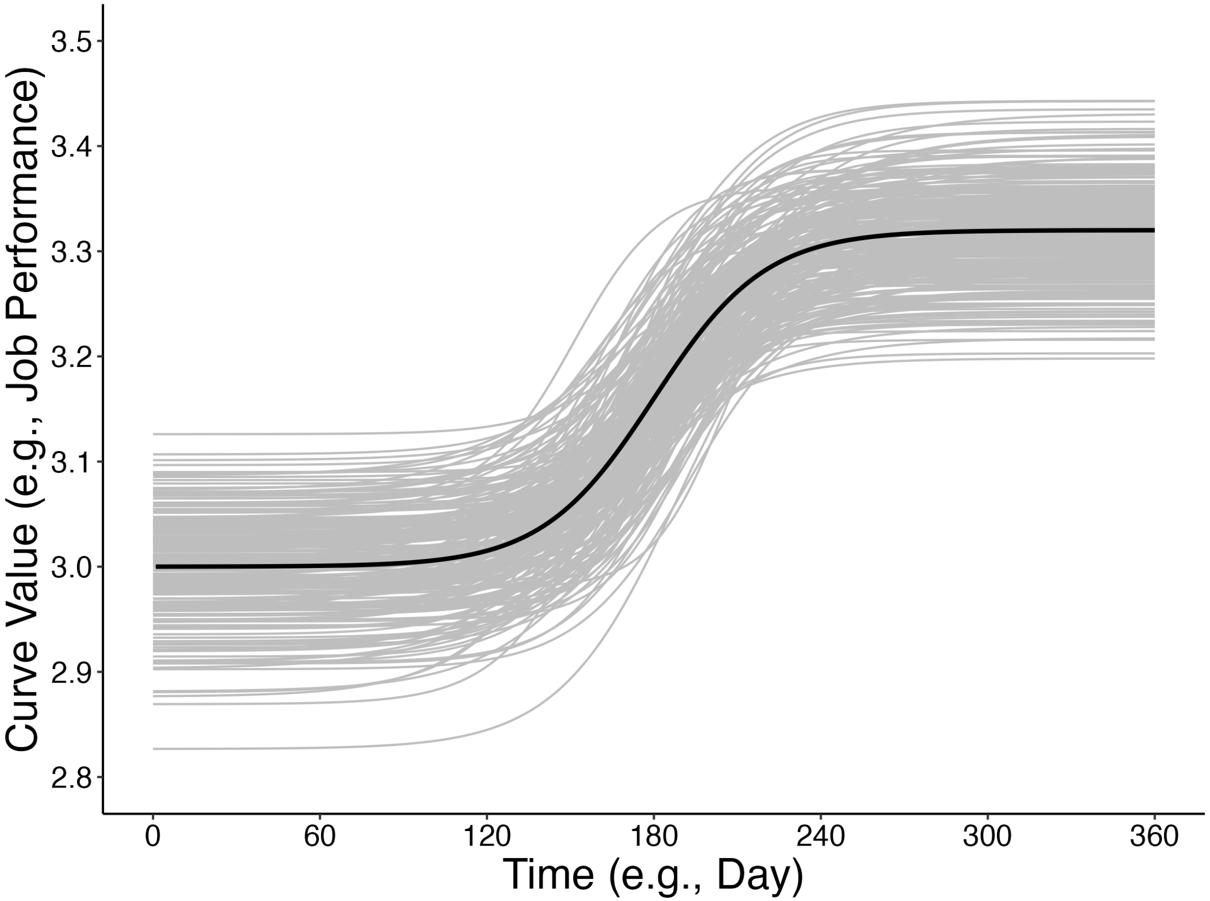
The Monte Carlo method: Population definition



Random effects (grey curves)*

1. Baseline (θ) = 0.05
2. Maximal elevation (α) = 0.05
3. Days to halfway elevation (β)= 10.00
4. Triquarter-halfway delta (γ) = 4.00

*random effects are given in standard deviation units

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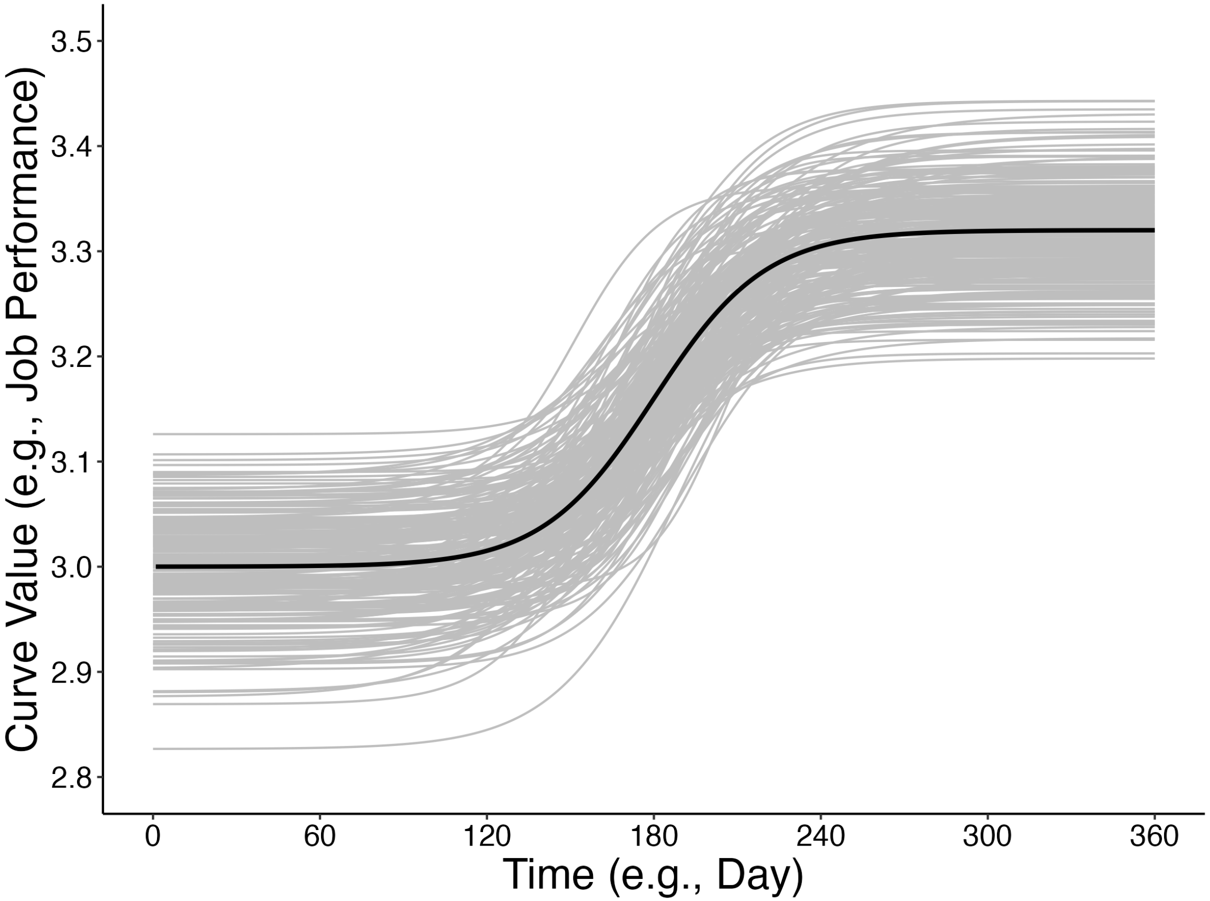
The Monte Carlo method: Population definition



Fixed effects (black curve)

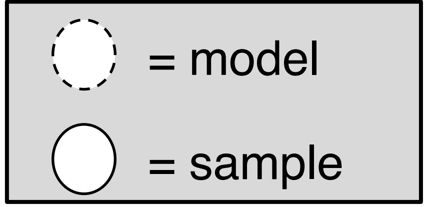
1. Baseline (θ) = 3.00
2. Maximal elevation (α) = 3.32
3. Days to halfway elevation (β)= 180.00
4. Triquarter-halfway delta (γ) = 20.00

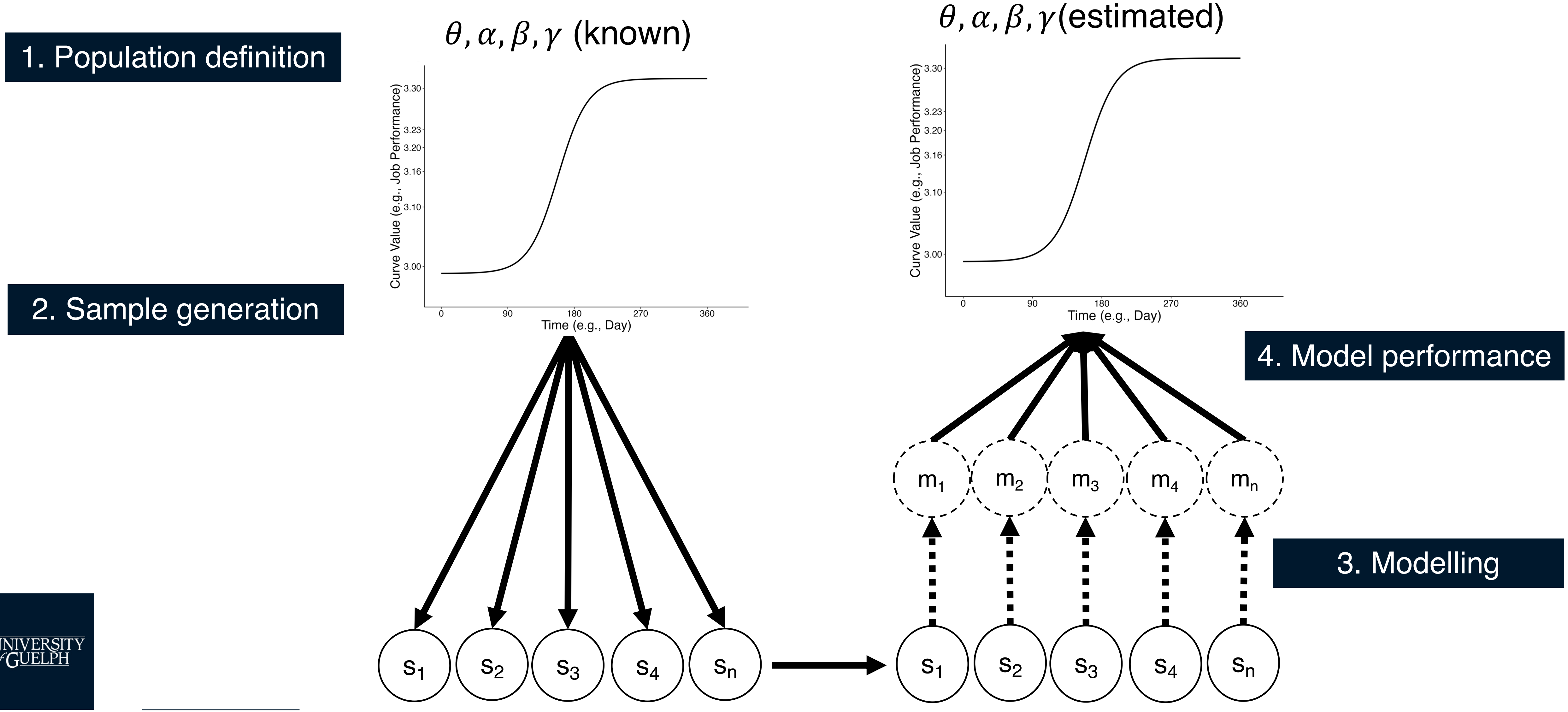
Random effects (*grey curves)

1. Baseline (θ) = 0.05
2. Maximal elevation (α) = 0.05
3. Days to halfway elevation (β) = 10.00
4. Triquarter-halfway delta (γ) = 4.00

*random effects are given in standard deviation units

The Monte Carlo method





The Monte Carlo method

= model

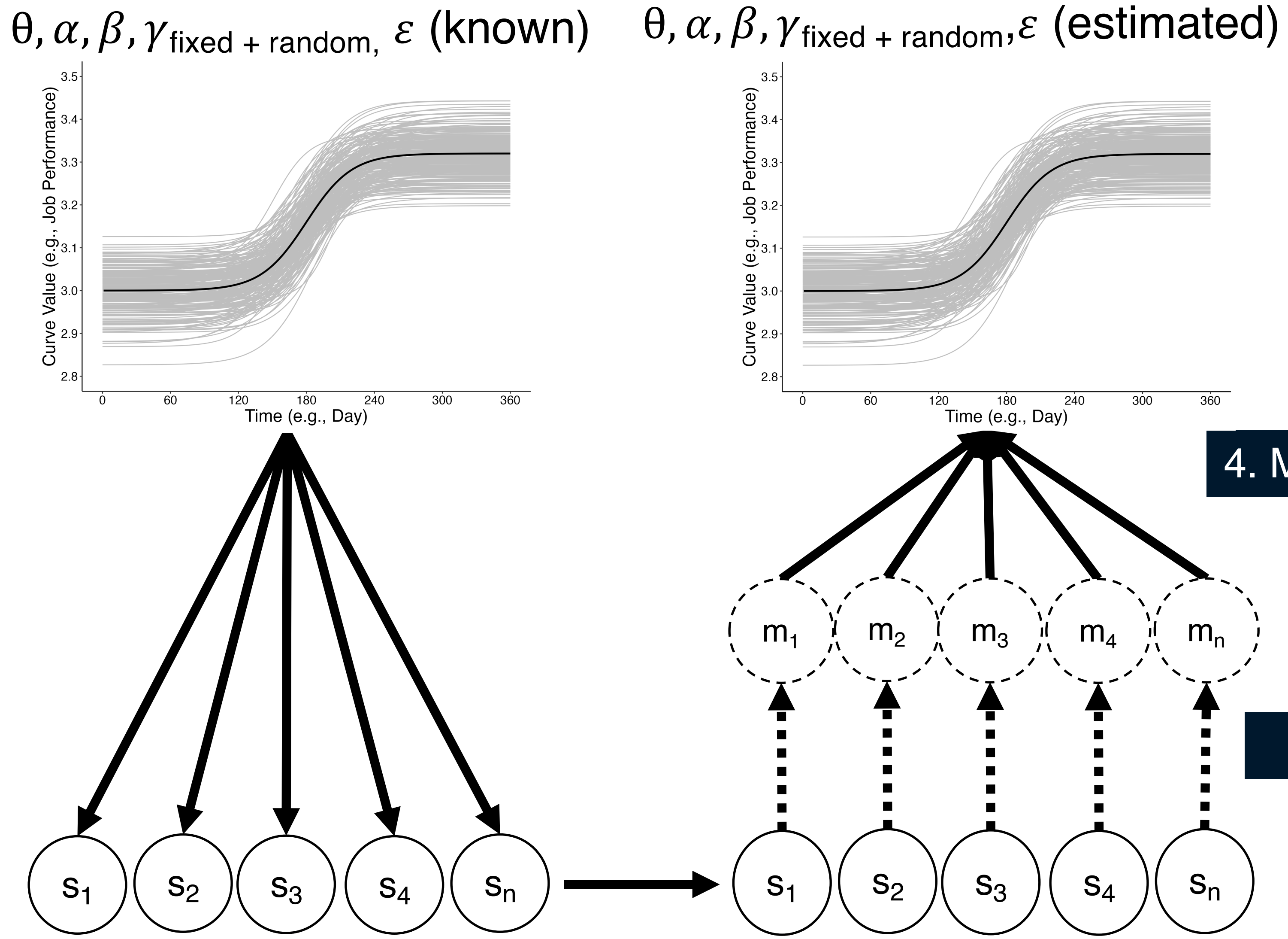
= sample

1. Population definition

2. Sample generation

3. Modelling

4. Model performance



Independent variable I: Nature of change

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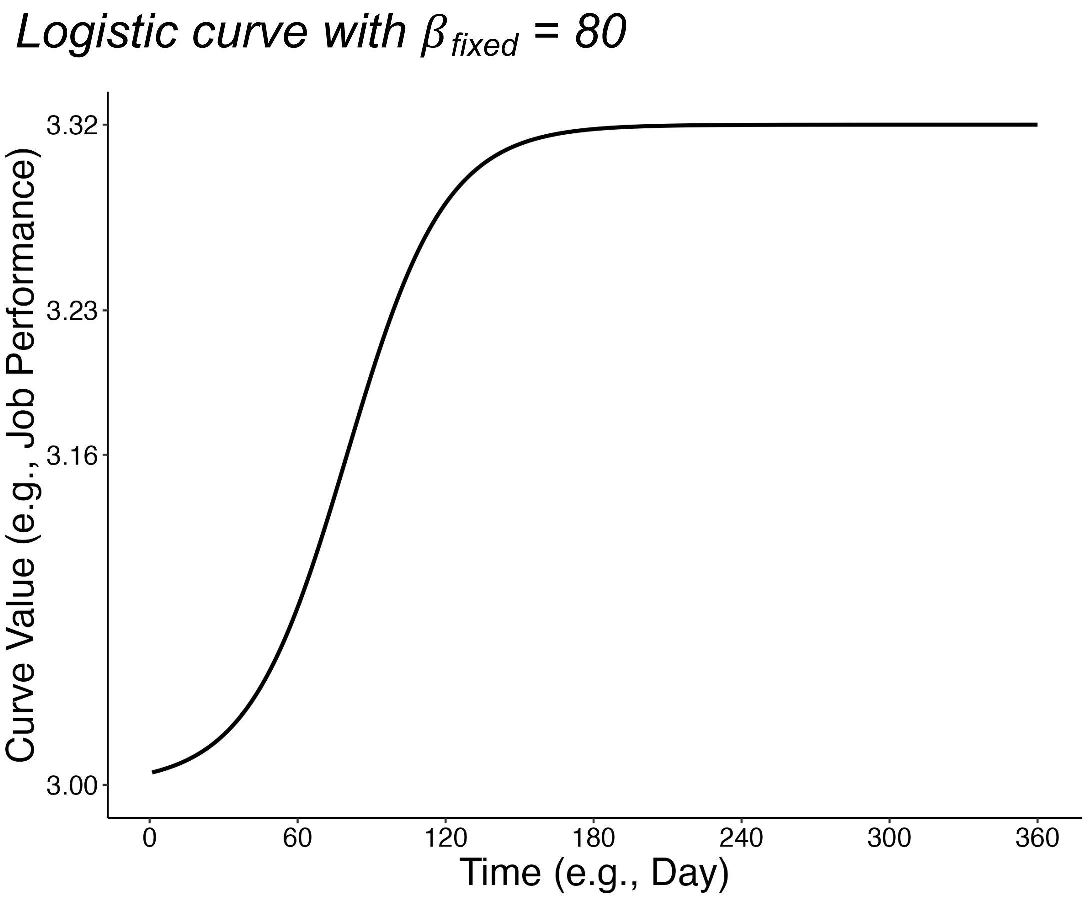
Question 2: How to space measurements when the nature of change is unknown?

Independent variable I: Nature of change



Question 2: How to space measurements when the nature of change is unknown?

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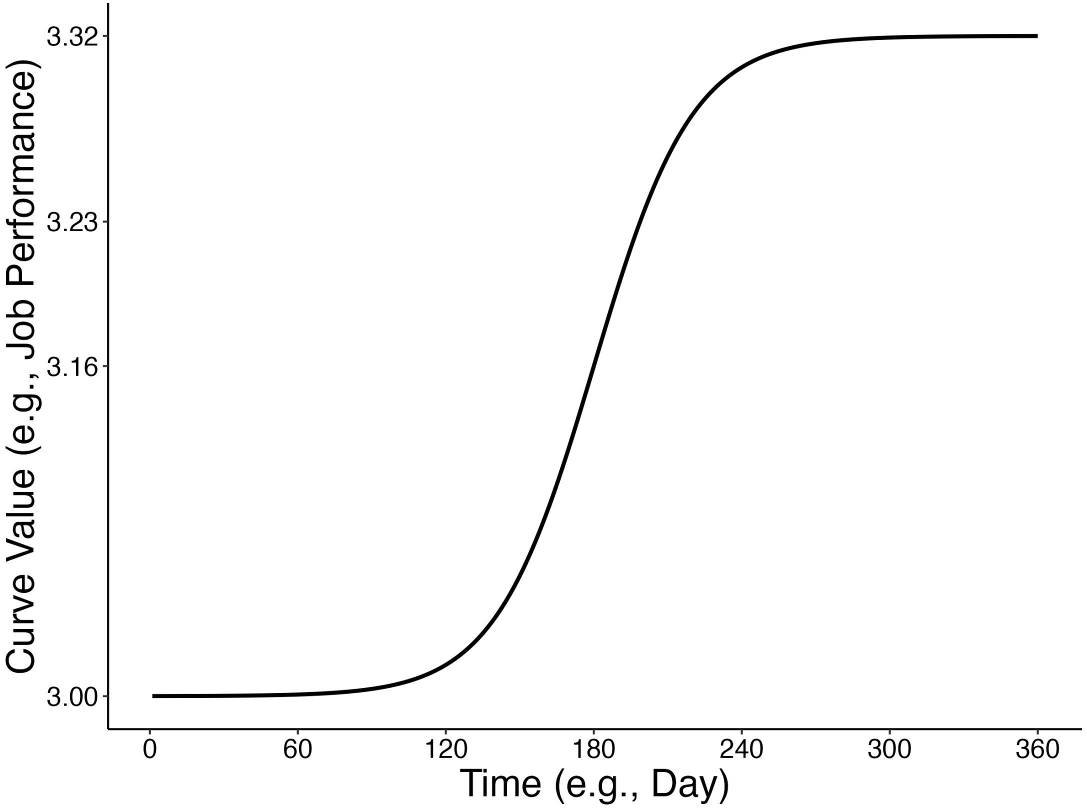
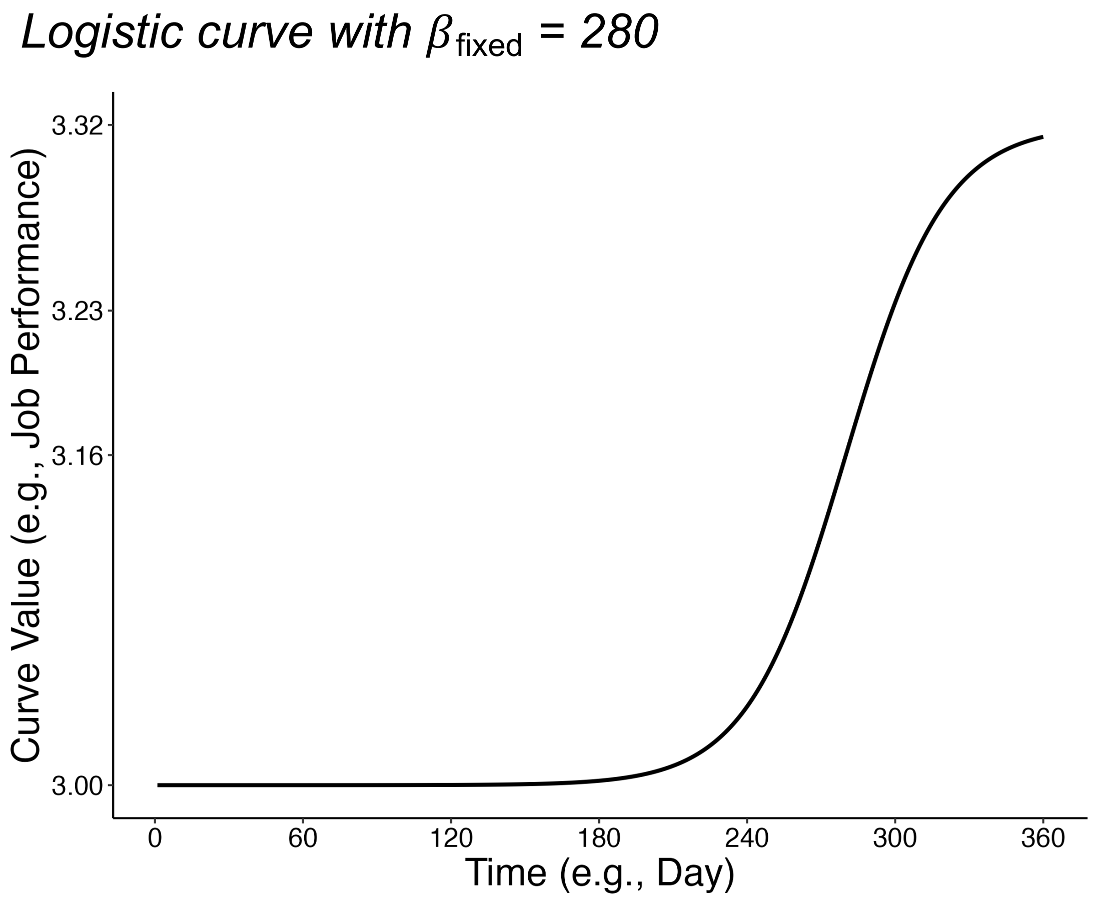
Independent variable I: Nature of change

Logistic curve with β_{fixed} = 180



Question 2: How to space measurements when the nature of change is unknown?

Independent variable I: Nature of change



Question 2: How to space measurements when the nature of change is unknown?

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The Monte Carlo method

= model

= sample

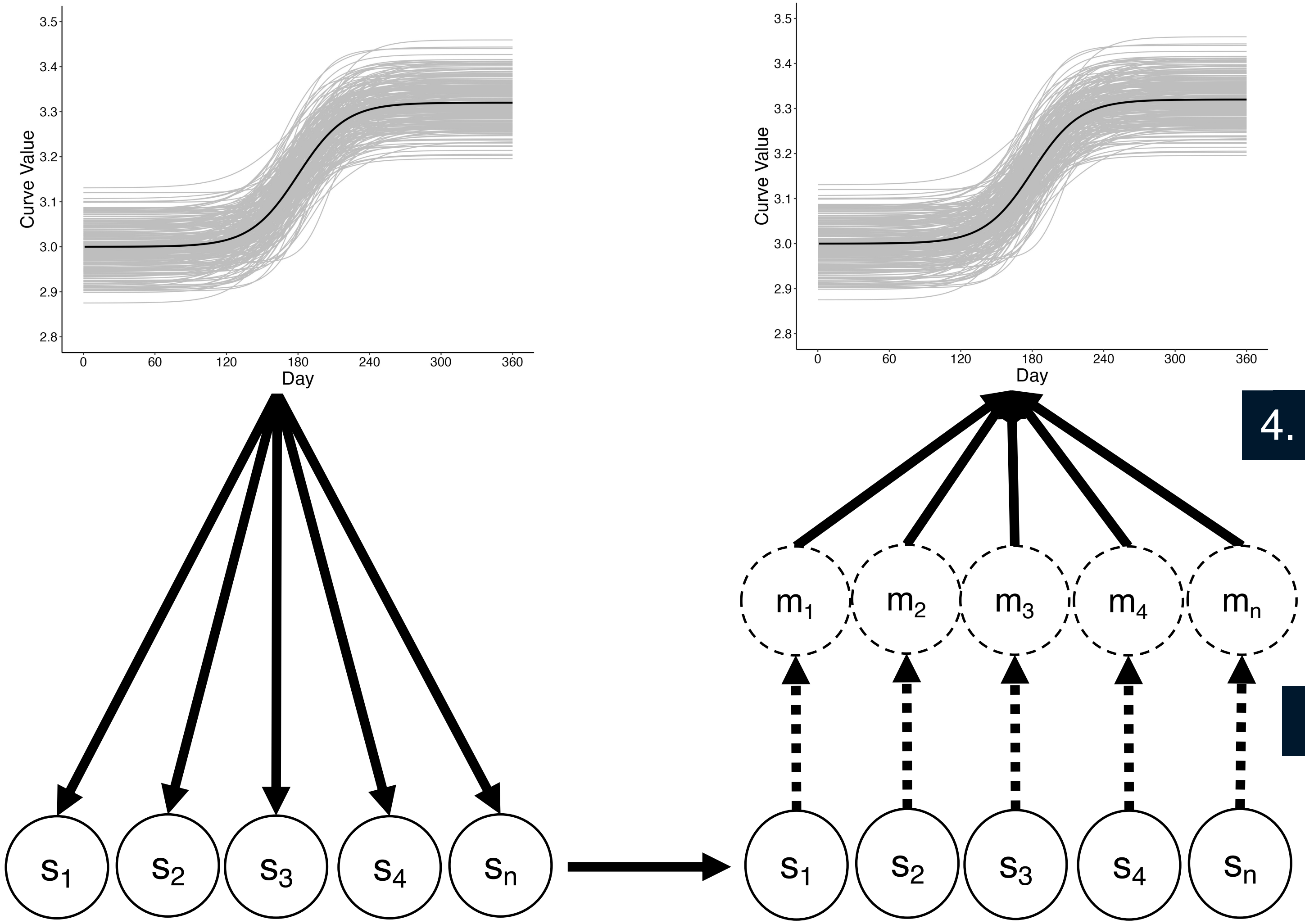
1. Population definition

IV 1: Nature of change
(β_{fixed} = *80, 180, or 280)*

2. Sample generation

$\theta, \alpha, \beta, \gamma_{\text{fixed + random}}, \varepsilon$ (known)

$\theta, \alpha, \beta, \gamma_{\text{fixed + random}}, \varepsilon$ (estimated)



4. Model performance

3. Modelling

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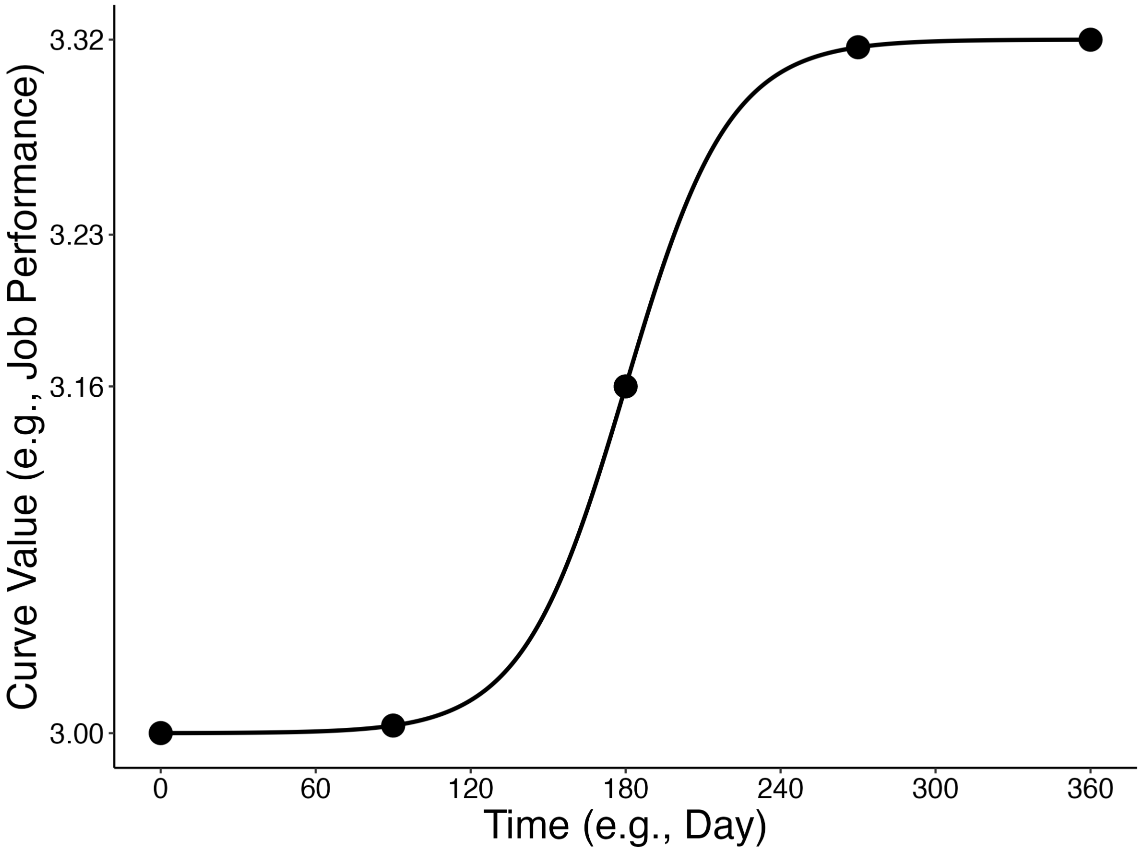
Independent variable II: Number of measurements

Independent variable II: Number of measurements

Five measurements



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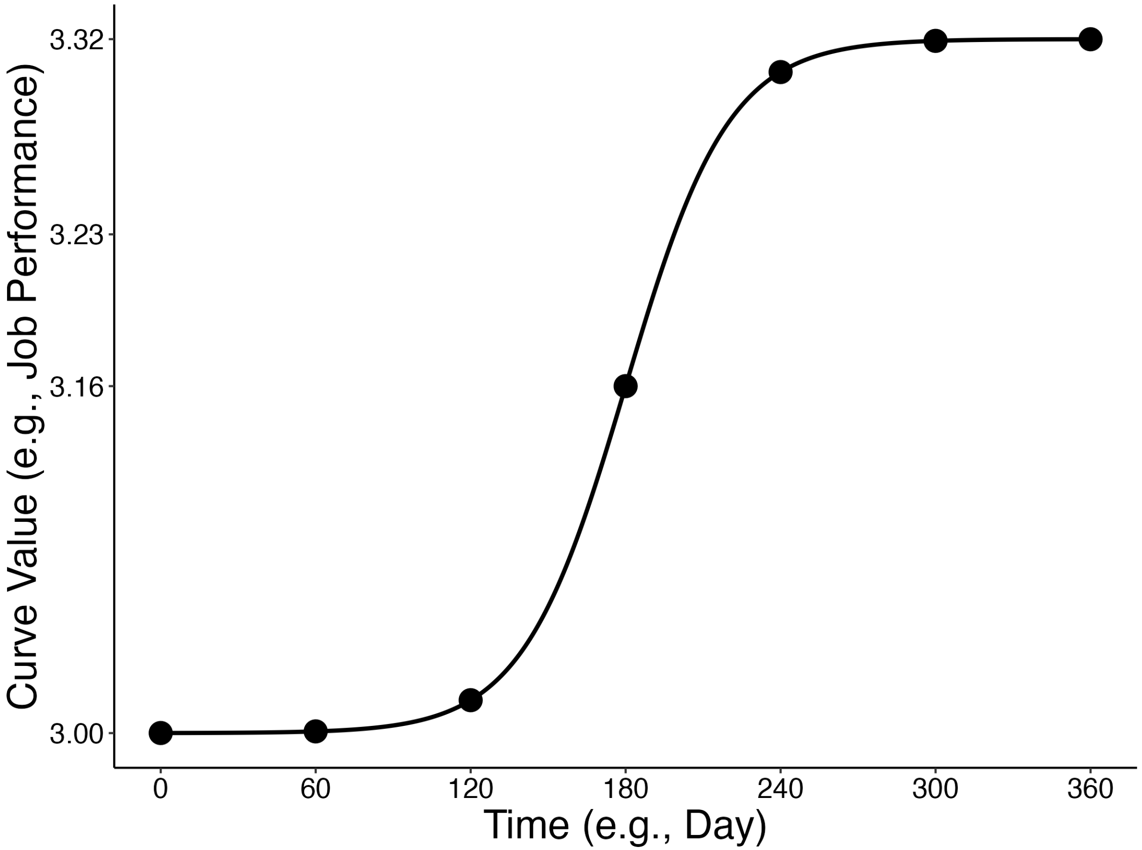
Independent variable II: Number of measurements

Seven measurements



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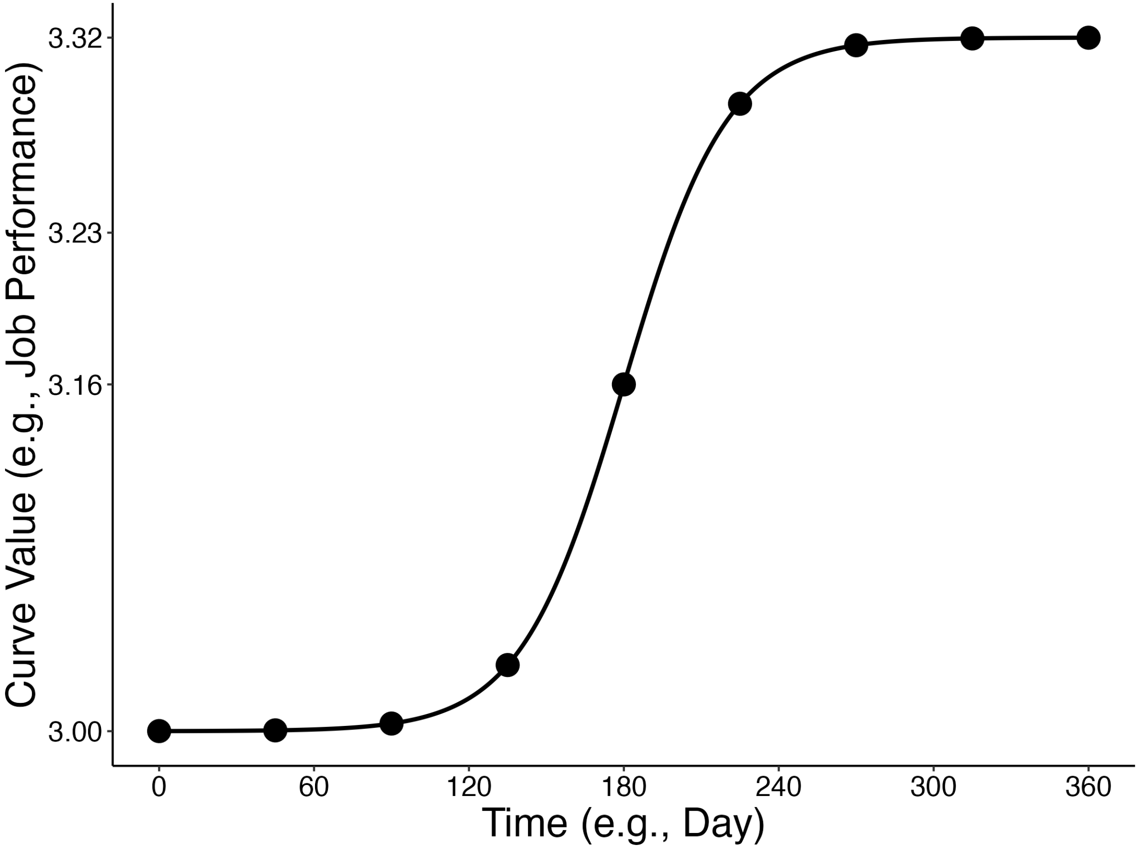
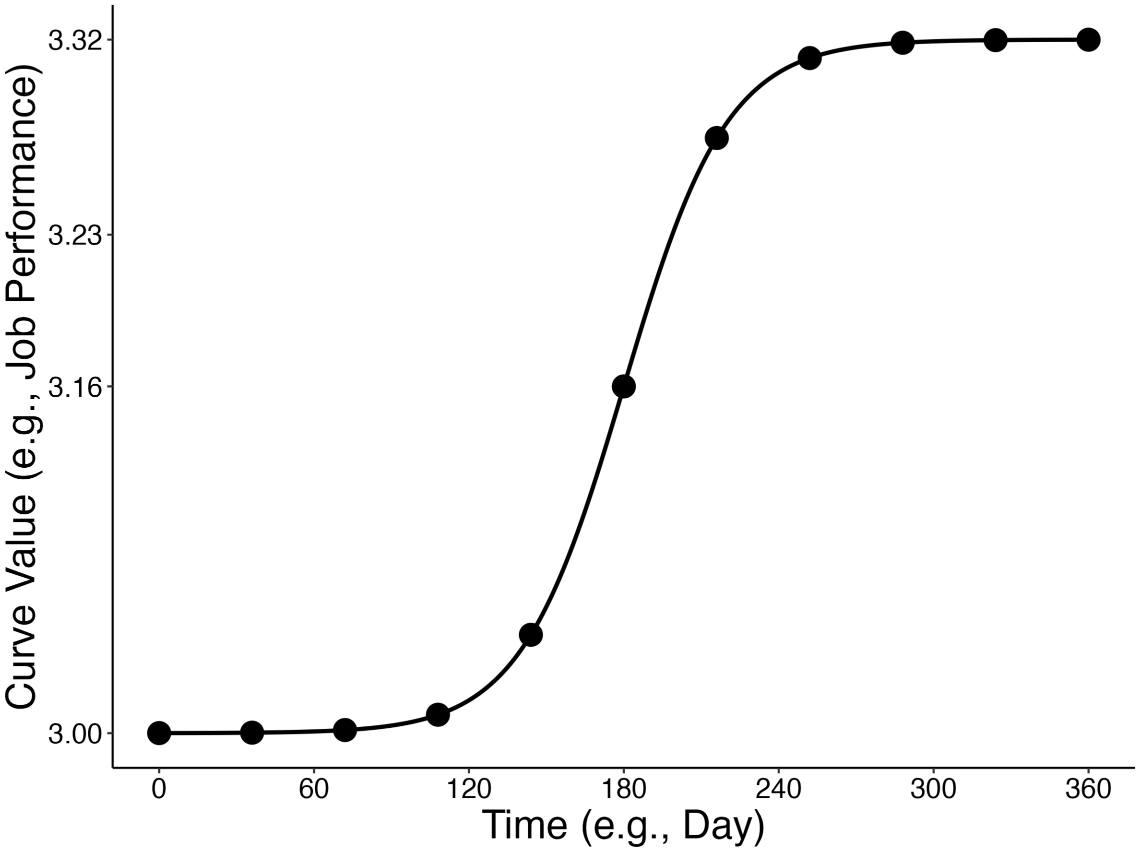
Independent variable II: Number of measurements

Nine measurements



Independent variable II: Number of measurements

Eleven measurements



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The Monte Carlo method

1. Population definition

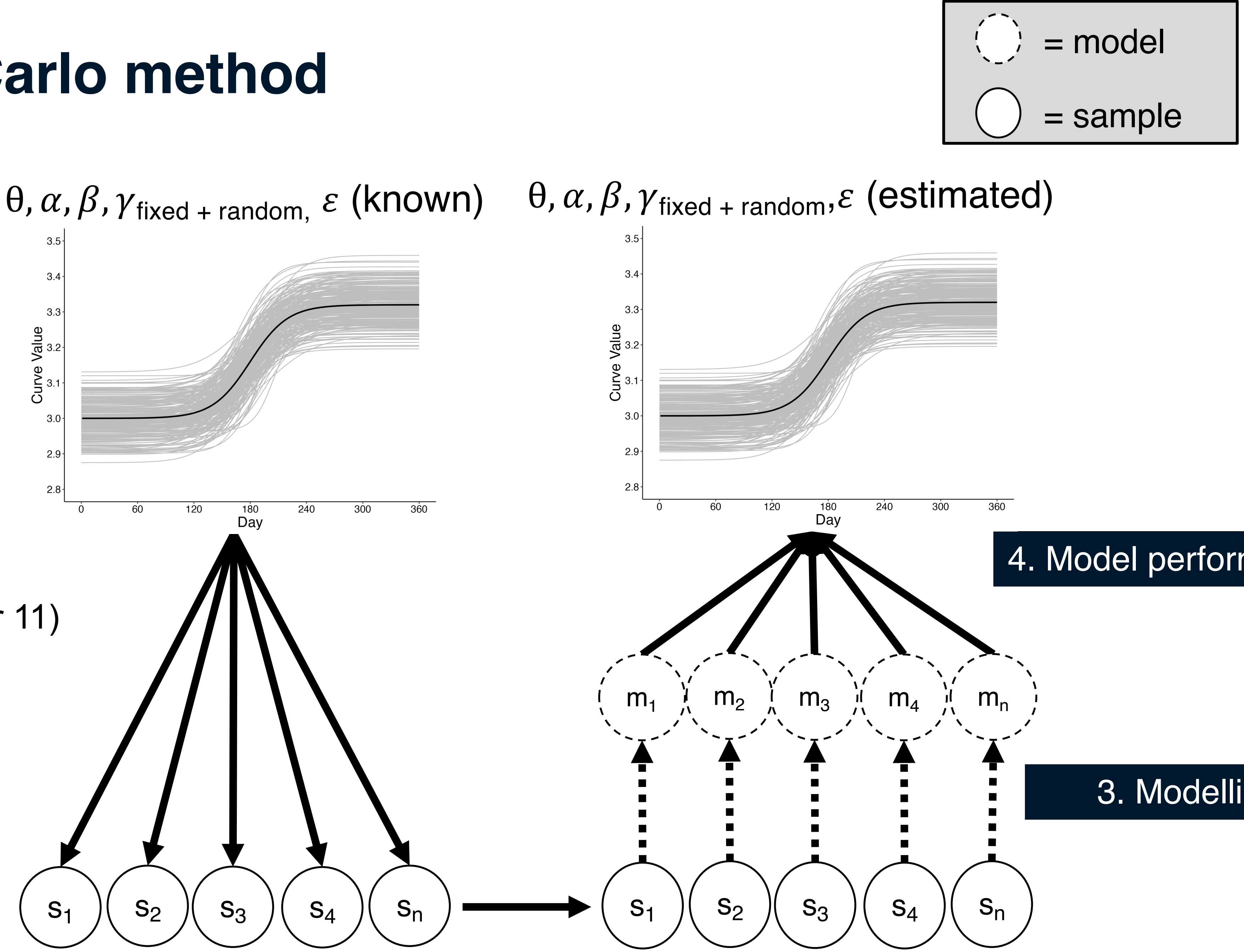
IV 1: Nature of change (β_{fixed} = *80, 180, or 280)*

2. Sample generation

IV 2: Number of measurements (5, 7, 9, or 11)

3. Modelling

4. Model performance



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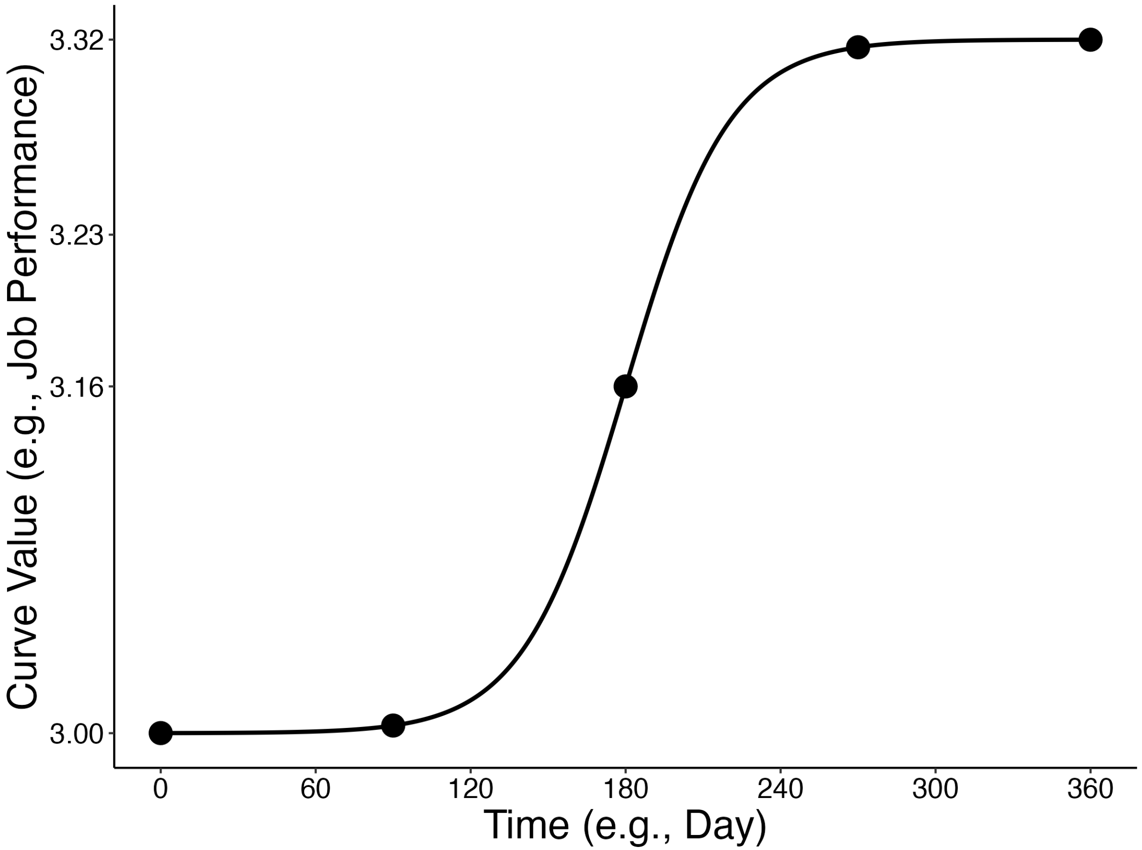
Independent variable III: Measurement spacing

Question 2: How to space measurements when the nature of change is unknown?

Independent variable III: Measurement spacing

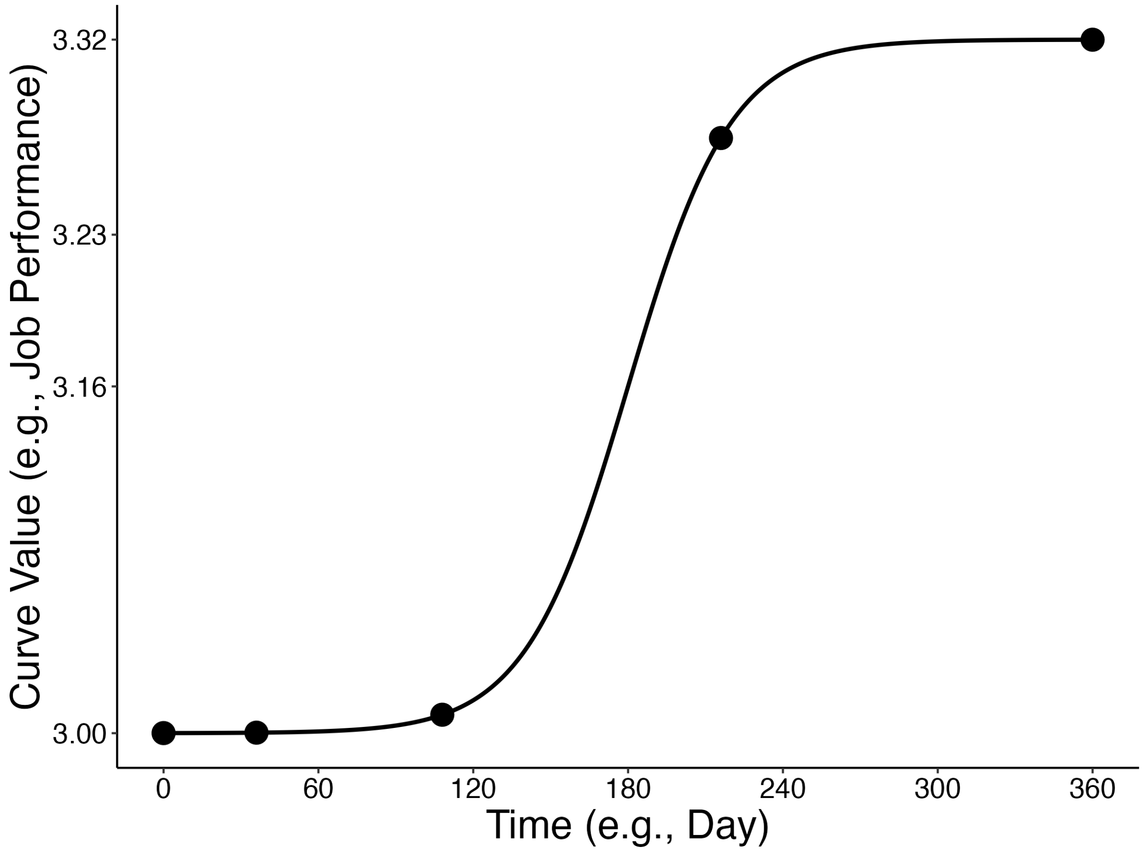
Equal spacing



Question 2: How to space measurements when the nature of change is unknown?

Independent variable III: Measurement spacing

Time-interval increasing spacing



Question 2: How to space measurements when the nature of change is unknown?

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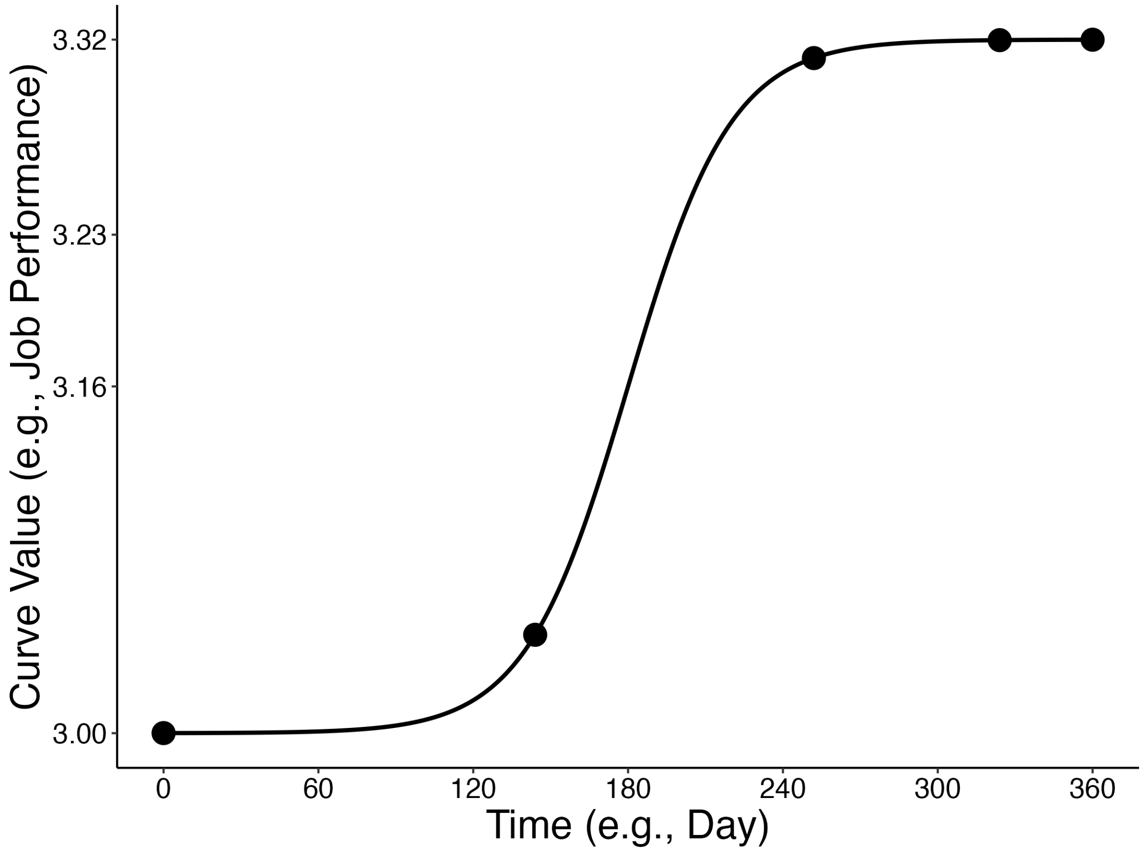
Independent variable III: Measurement spacing

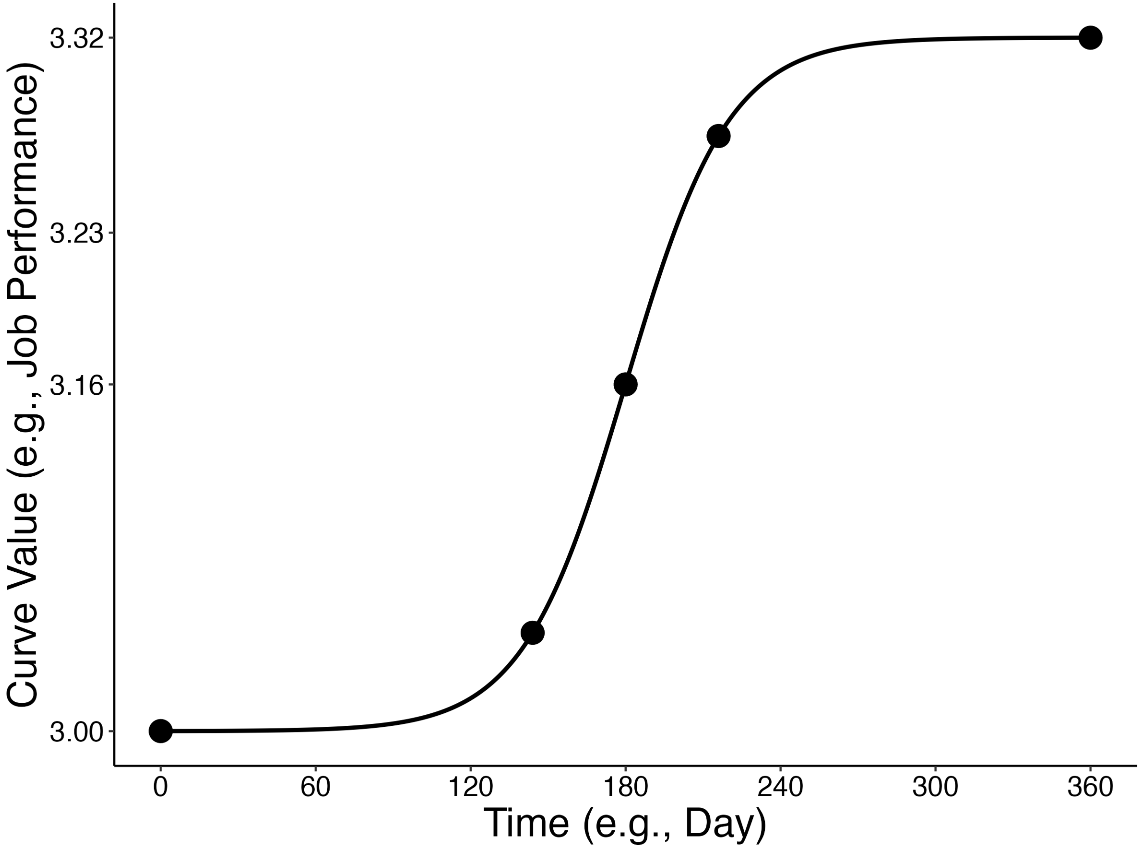
Time-interval decreasing spacing



Question 2: How to space measurements when the nature of change is unknown?

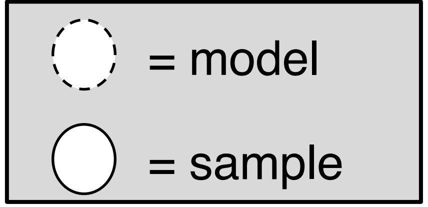
Independent variable III: Measurement spacing

Middle-and-extreme spacing



Question 2: How to space measurements when the nature of change is unknown?

The Monte Carlo method



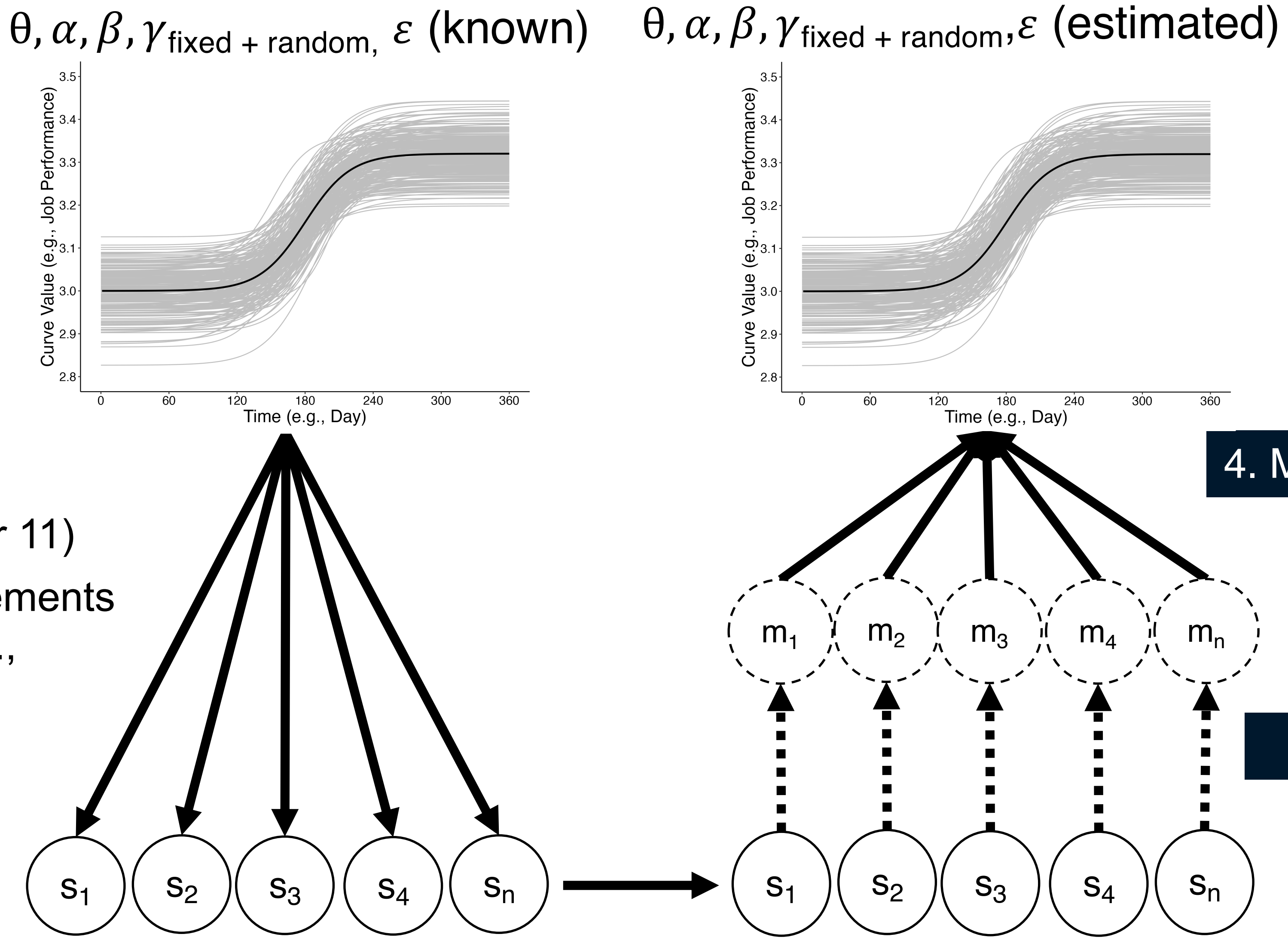
1. Population definition

IV 1: Nature of change (β_{fixed} = *80, 180, or 280)*

2. Sample generation

IV 2: Number of measurements (5, 7, 9, or 11)

IV 3: Spacing of measurements (equal, time-in., time-dec., middle-and-extreme)



4. Model performance

3. Modelling

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Monte Carlo method: Modelling

Browne (1993); Browne & du Toit (1991);

Monte Carlo method: Modelling

Structured latent growth curve model

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Browne (1993); Browne & du Toit (1991);

Monte Carlo method: Modelling

Structured latent growth curve model = latent growth curve model

+

Taylor series approximations

Browne (1993); Browne & du Toit (1991);

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The Monte Carlo method

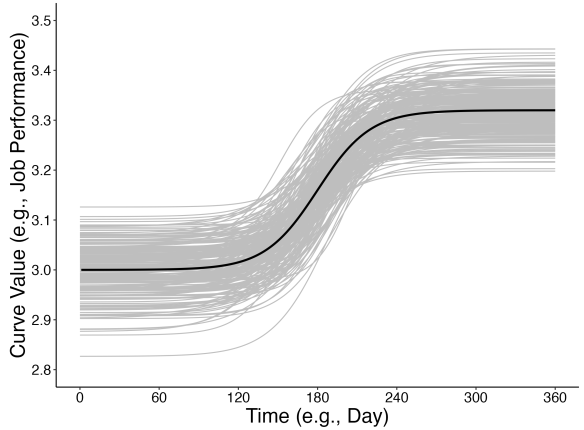
= model

= sample

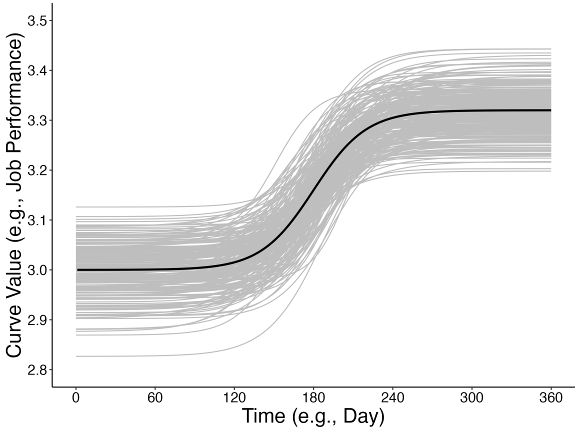
1. Population definition

IV 1: Nature of change (β_{fixed} = 80, 180, 280)

$\theta, \alpha, \beta, \gamma_{\text{fixed + random}}, \varepsilon$ (known)



$\theta, \alpha, \beta, \gamma_{\text{fixed + random}}, \varepsilon$ (estimated)

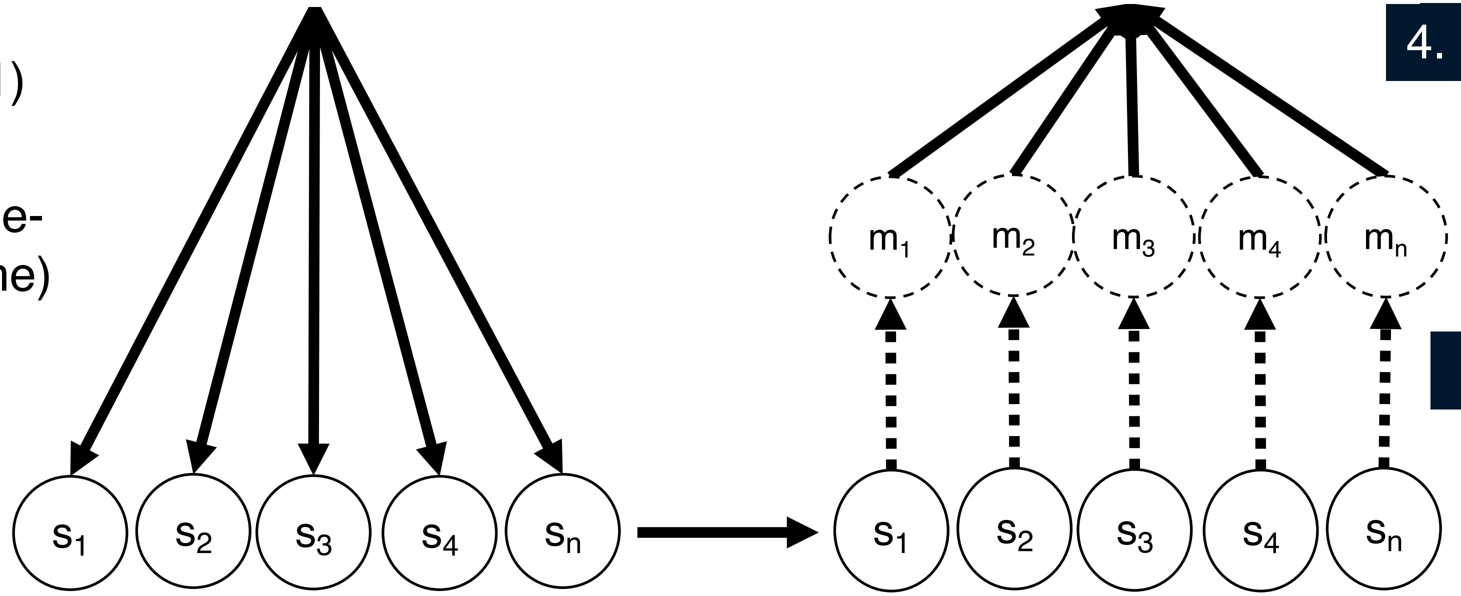


2. Sample generation

IV 2: Number of measurements (5, 7, 9, 11)

IV 3: Spacing of measurements (equal, time-inc., time dec., mid-extreme)

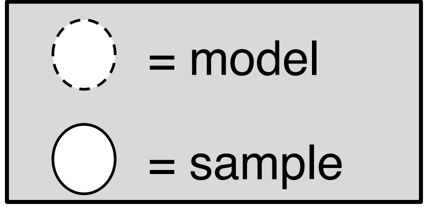
4. Model performance



3. Modelling

Structured latent growth model

The Monte Carlo method



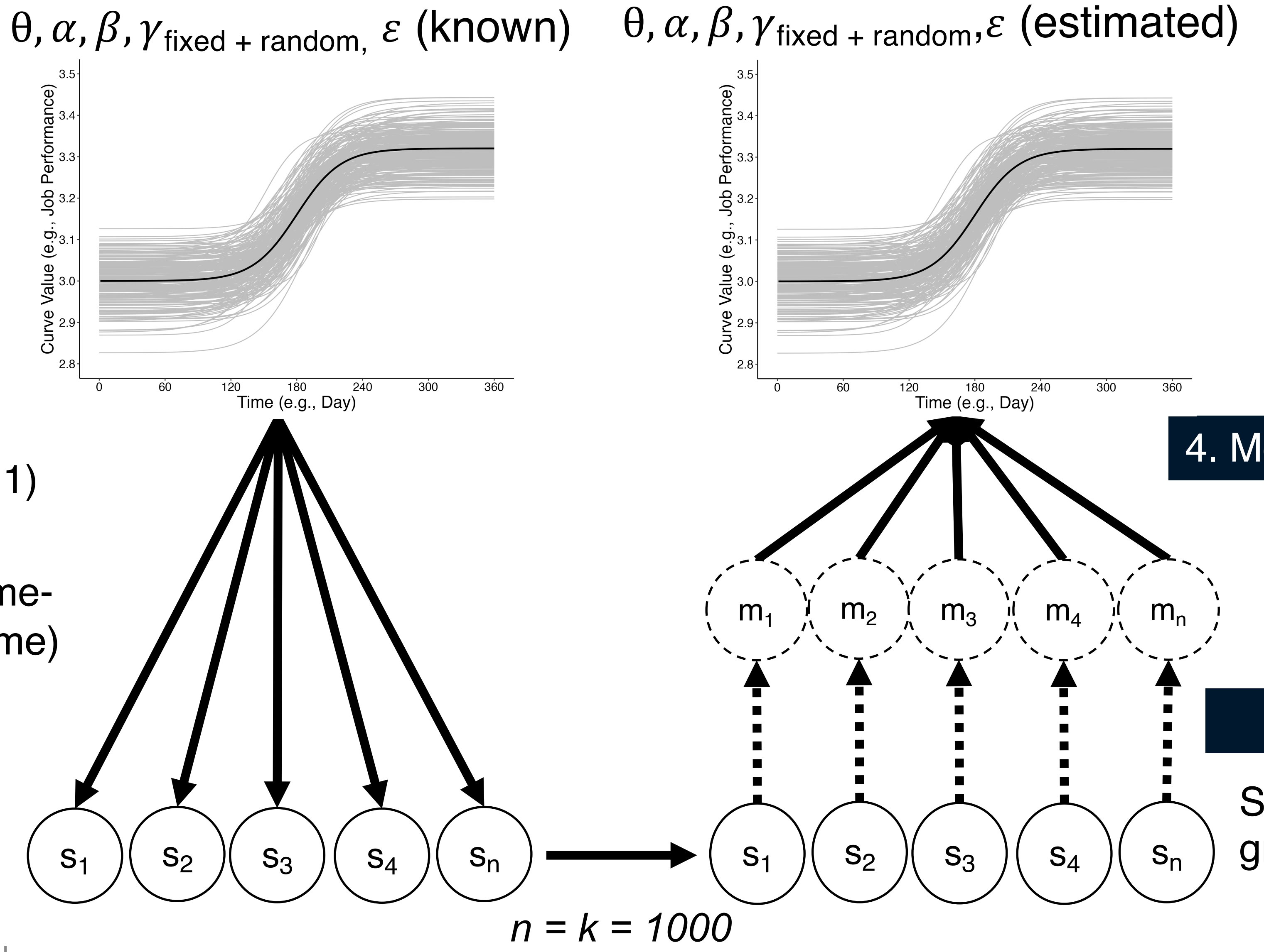
1. Population definition

IV 1: Nature of change (β_{fixed} = 80, 180, 280*)*

2. Sample generation

IV 2: Number of measurements (5, 7, 9, 11)

IV 3: Spacing of measurements (equal, time-inc., time dec., mid-extreme)



4. Model performance

3. Modelling

Structured latent growth model

Experiment 1

Question 1: Does placing measurements near periods of change increase model performance?

Question 2: How to space measurements when the nature of change is unknown?

Experiment 1

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Experiment 1

Question 1: Does placing measurements near periods of change increase model performance?

Question 2: How to space measurements when the nature of change is unknown?

IV 1: Nature of change (β_{fixed} = 80, 180, 280*)*

IV 2: Number of measurements (5, 7, 9, 11)

IV 3: Spacing of measurements (equal, time-inc., time dec., mid-extreme)

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Experiment 1

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3 x 4 x 4

= **48** cells

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3 x 4 x 4

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1 cell

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3 x 4 x 4

= **48** cells

1 cell →

Nature of change (β_{fixed}) = 180

Number of measurements (NM) = 5

Spacing = time-interval increasing

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Experiment 1

Question 1: Does placing measurements near periods of change increase model performance?

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3 x 4 x 4

= **48** cells

1 cell ⟶ Nature of change (β_{fixed}) = 180
Number of measurements (NM) = 5
Spacing = time-interval increasing ⟶ Fixed-Effect Triquarter-Halfway Delta Parameter (γ_{fixed})

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Experiment 1

Question 1: Does placing measurements near periods of change increase model performance?

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3 x 4 x 4

= **48** cells

1 cell → Nature of change (β_{fixed}) = 180
Number of measurements (NM) = 5
Spacing = time-interval increasing
→ Fixed-Effect Triquarter-Halfway Delta Parameter (γ_{fixed})

m_1 m_2 m_3 m_4 m_n

n = k = 1000

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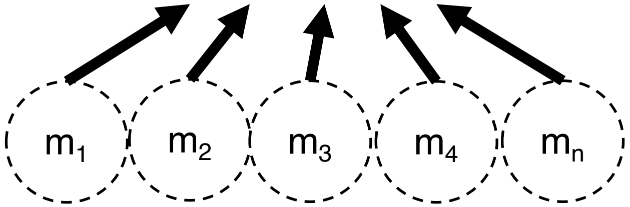
Monte Carlo method: Model performance

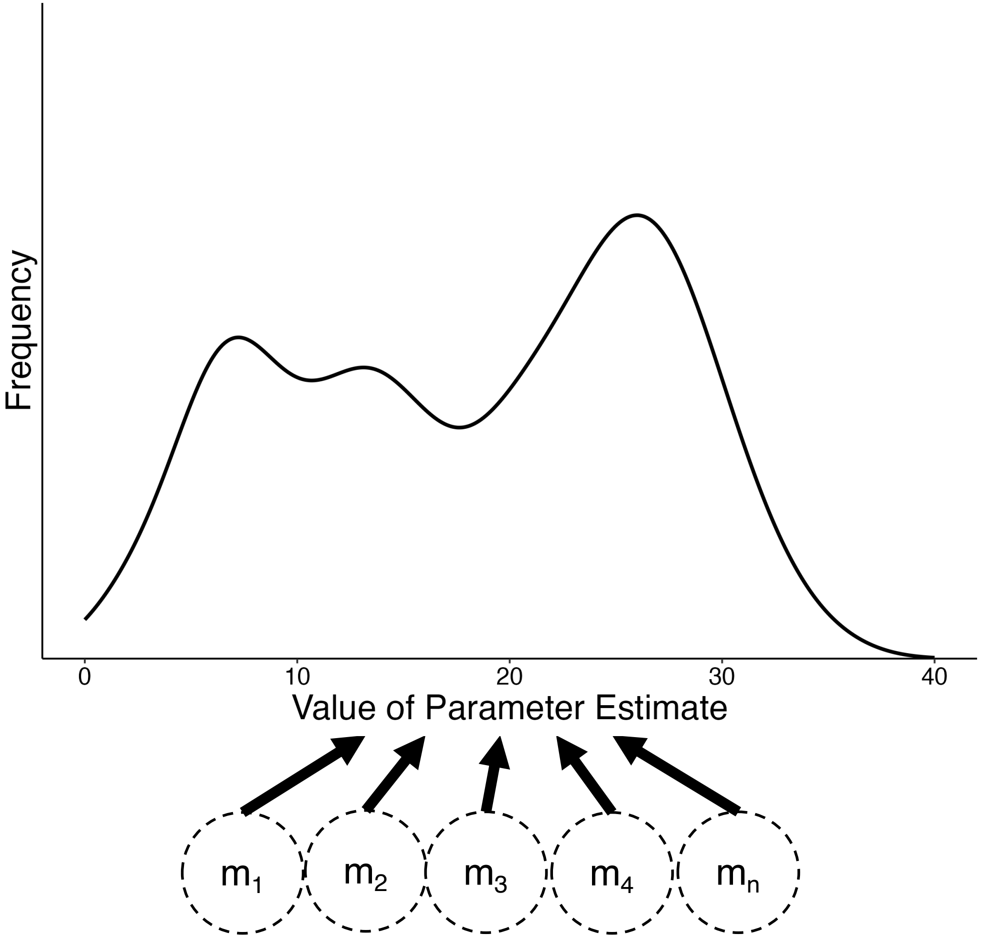
Values Estimated for Fixed-Effect Triquarter-Halfway Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



n = 1000

Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



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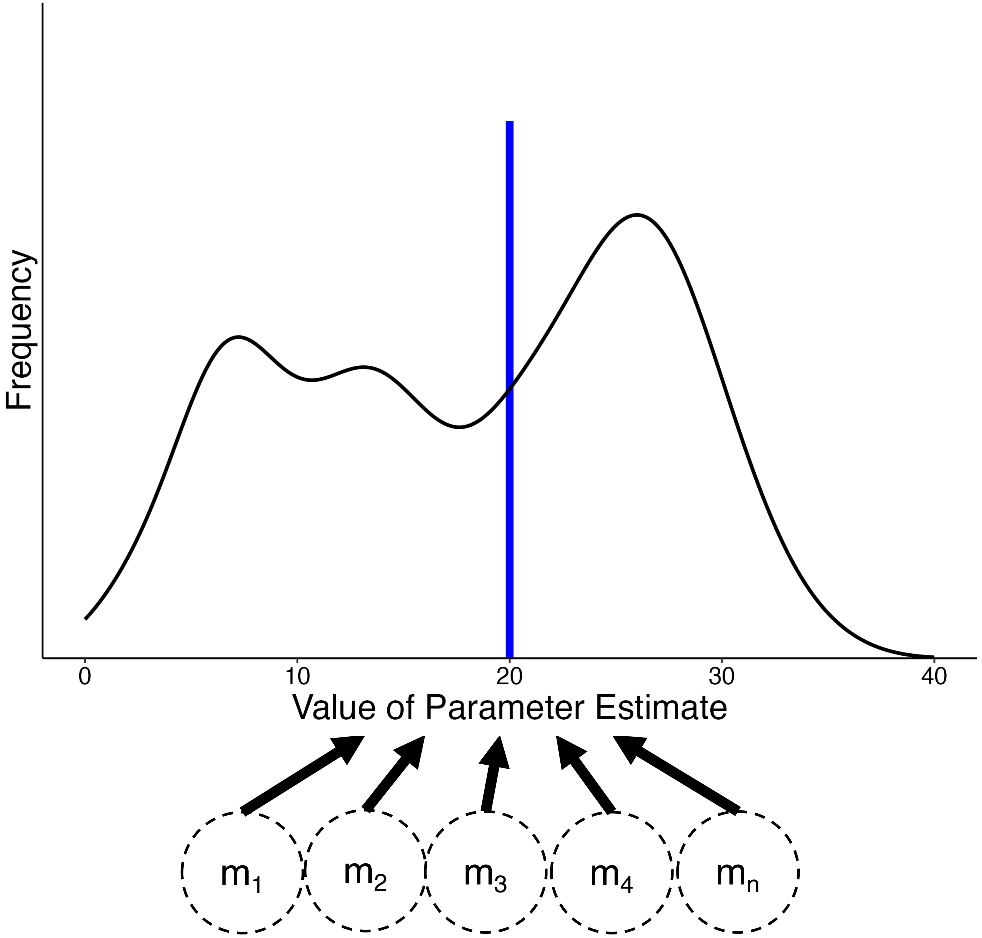
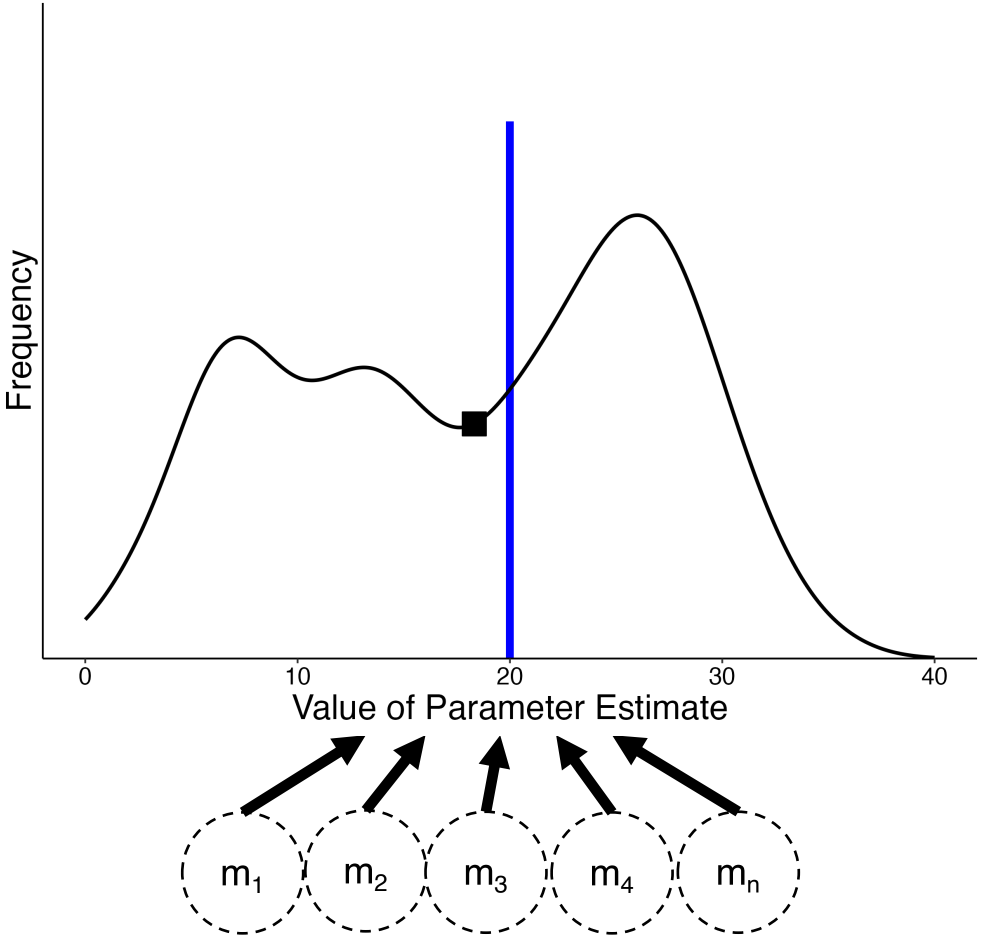
Values Estimated for Fixed-Effect Triquarter-Halfway Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



n = 1000

Monte Carlo method: Model performance

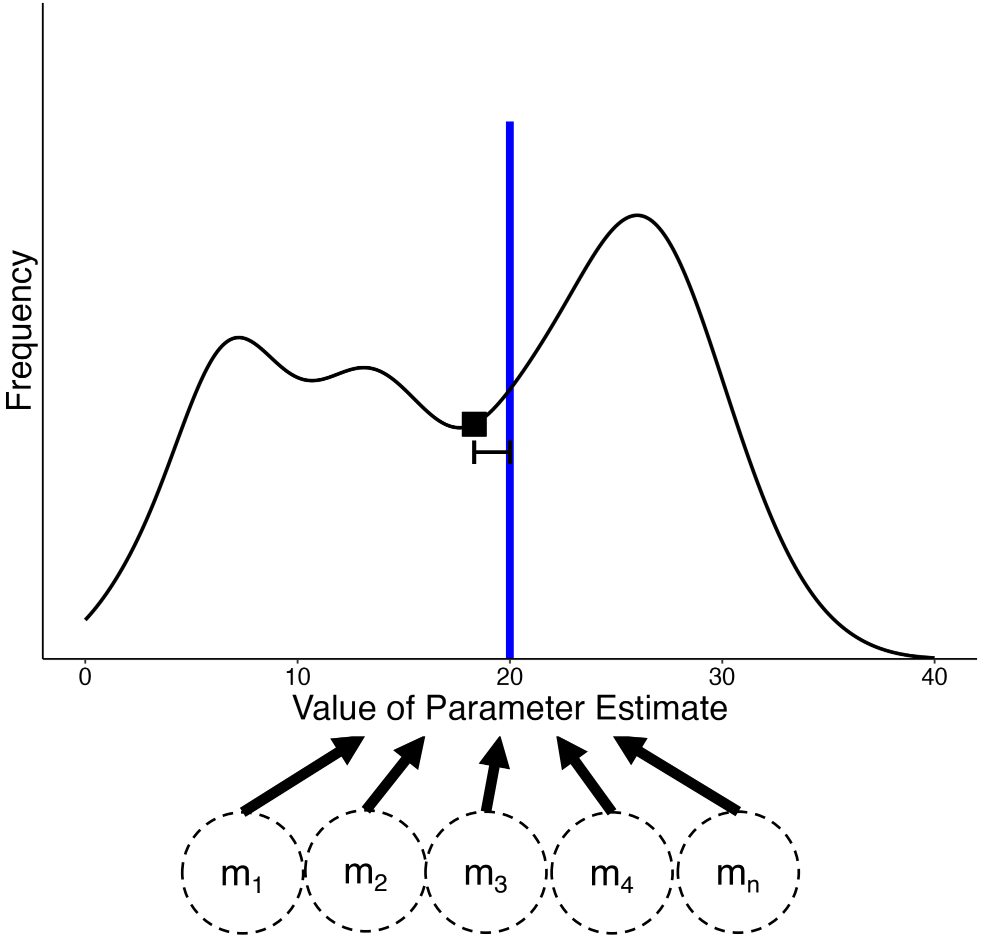
Values Estimated for Fixed-Effect Triquarter-Halfway Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



n = 1000

Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)

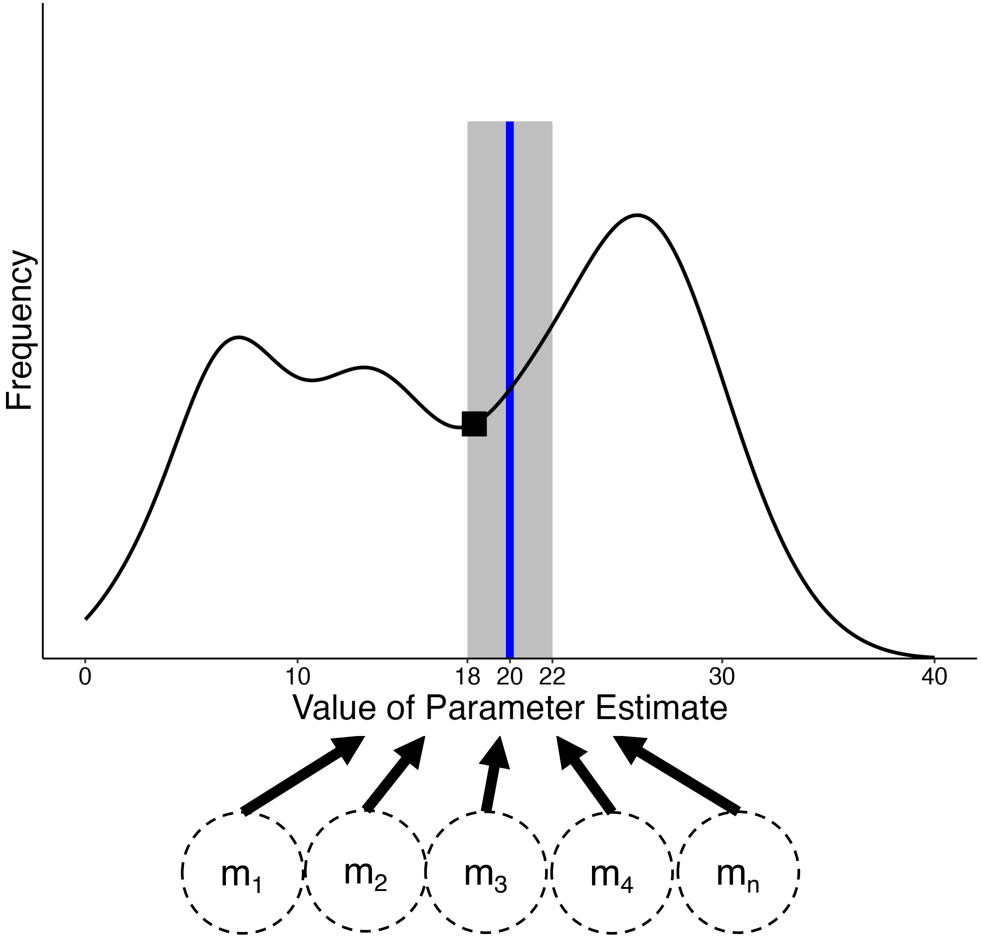


n = 1000

Bias: difference between average estimated value and population value

Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



n = 1000

Bias: difference between average estimated value and population value

Estimates were biased if bias > 10% of population value

Muthén et al. (1997)

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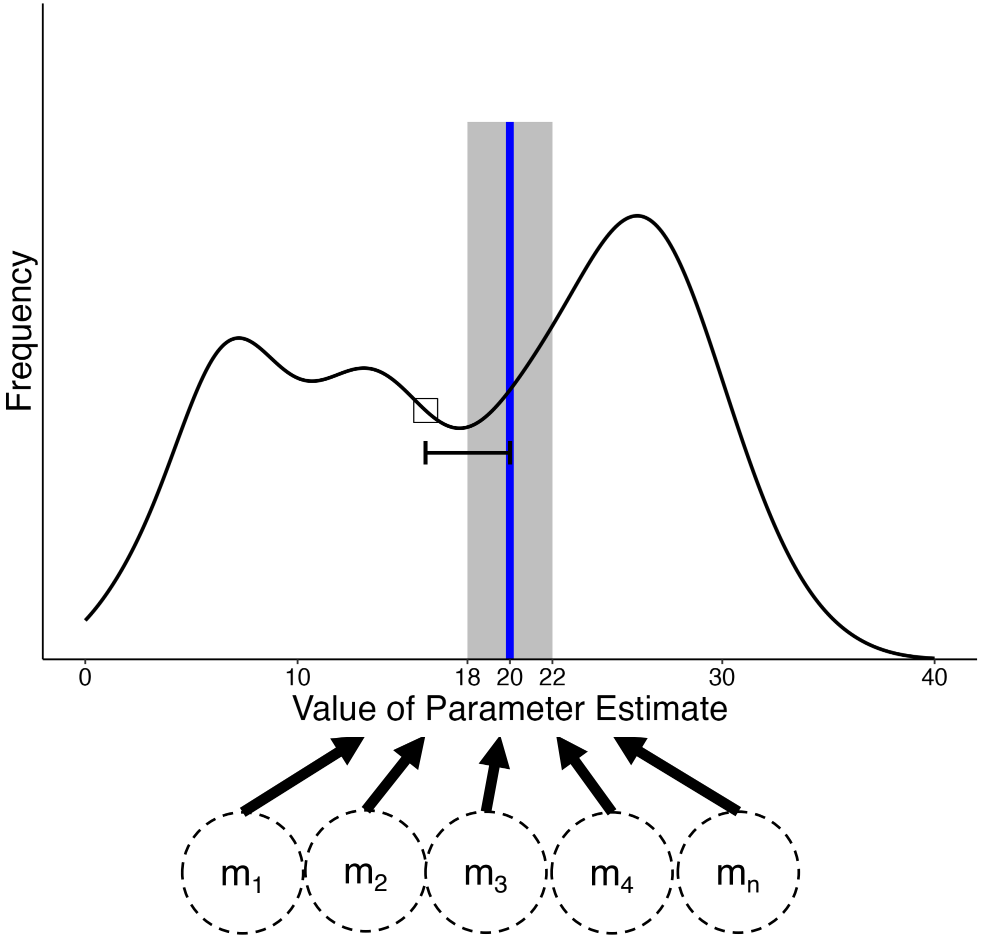
Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



n = 1000

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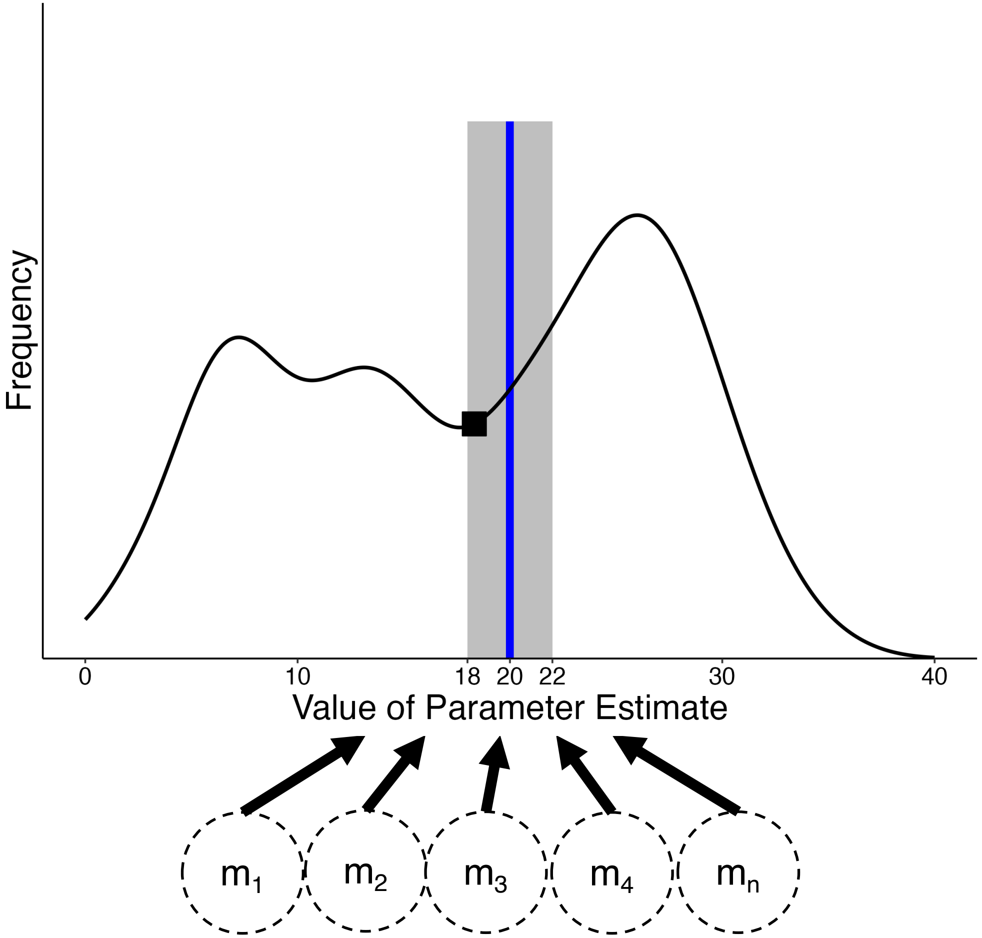
Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Parameter (γ_{fixed}; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



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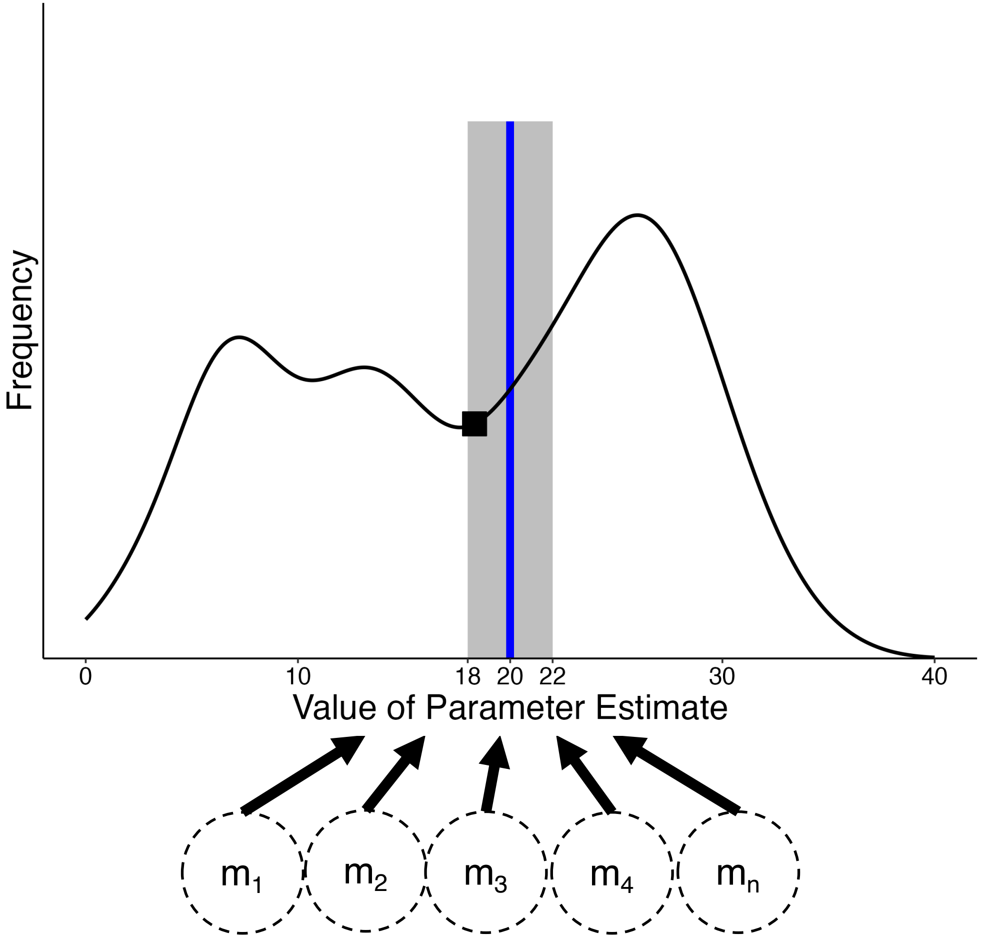

n = 1000

Bias: difference between average estimated value and population value

Estimates were biased if bias > 10% of population value

Precision: range of values covered by the middle 95% of estimates

Muthén et al. (1997)

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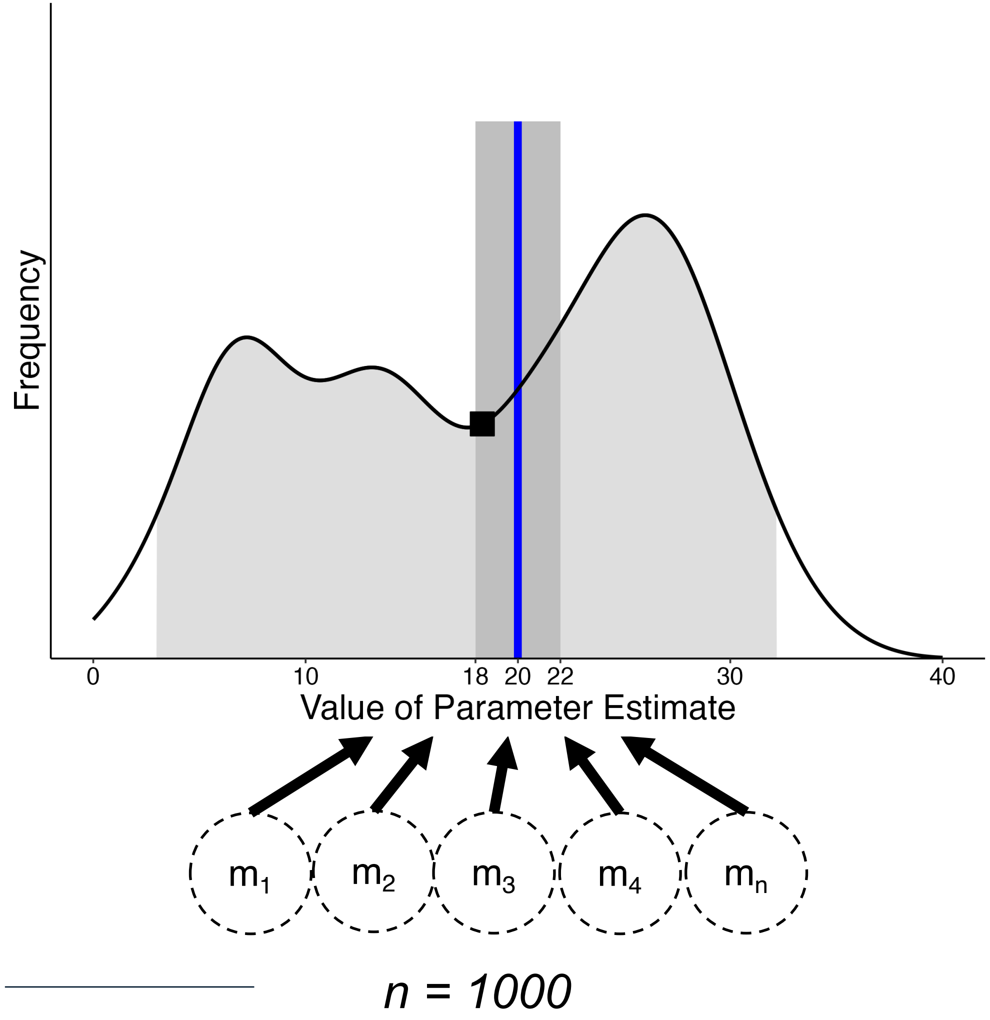
Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Parameter (γ_{fixed}; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



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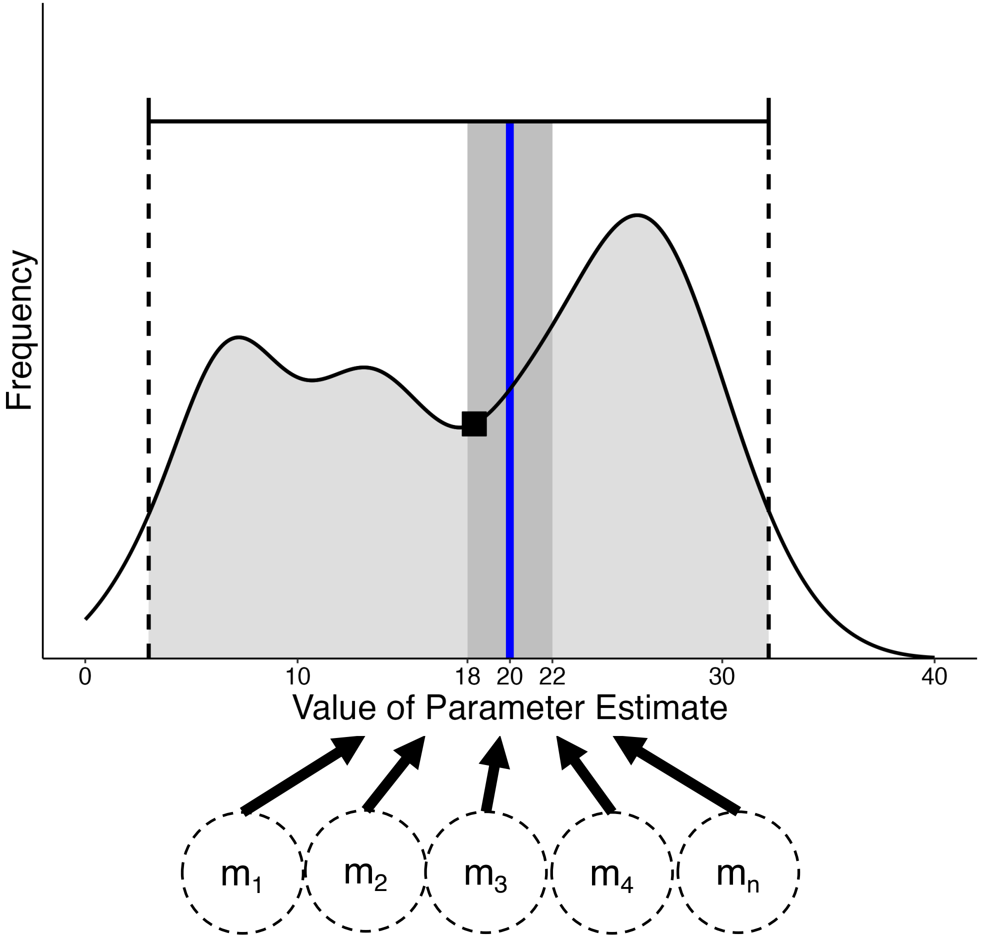

n = 1000

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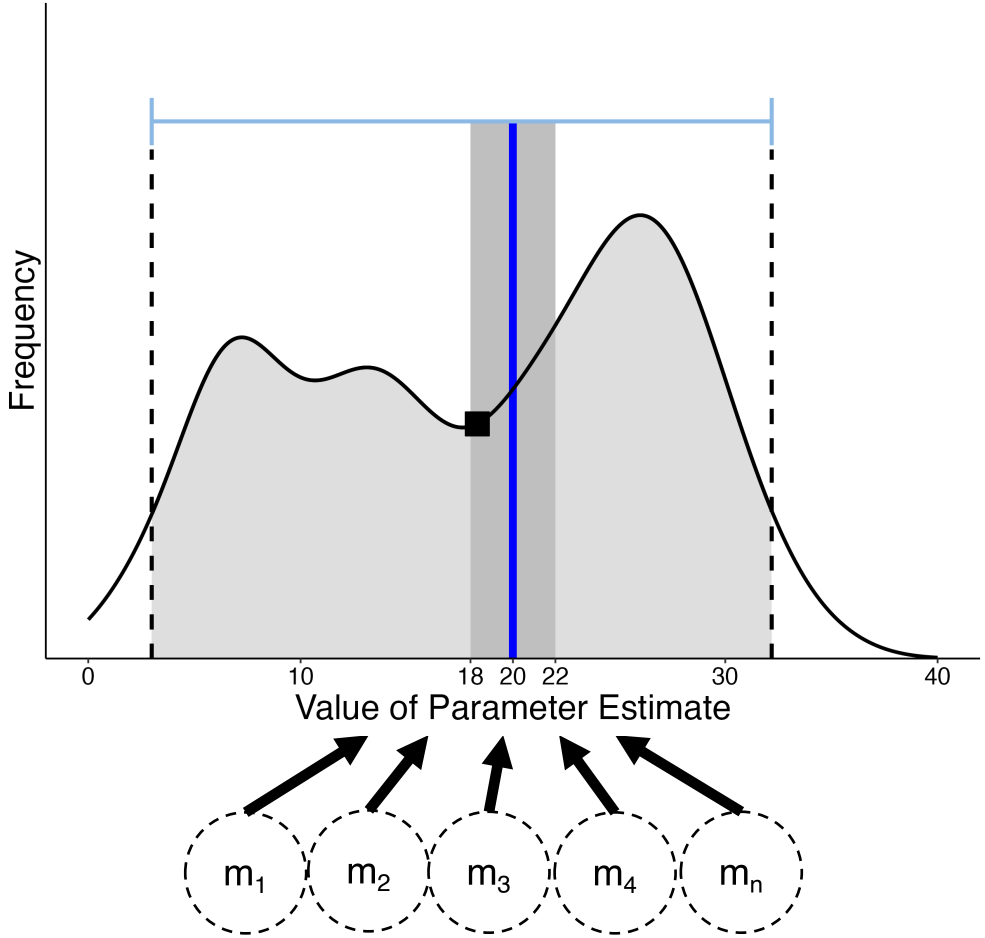
Estimates were biased if bias > 10% of population value

Precision: range of values covered by the middle 95% of estimates

Muthén et al. (1997)

Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



n = 1000

Bias: difference between average estimated value and population value

Estimates were biased if bias > 10% of population value

Precision: range of values covered by the middle 95% of estimates

Estimation was imprecise if a whisker length > 10% of population value

Muthén et al. (1997)

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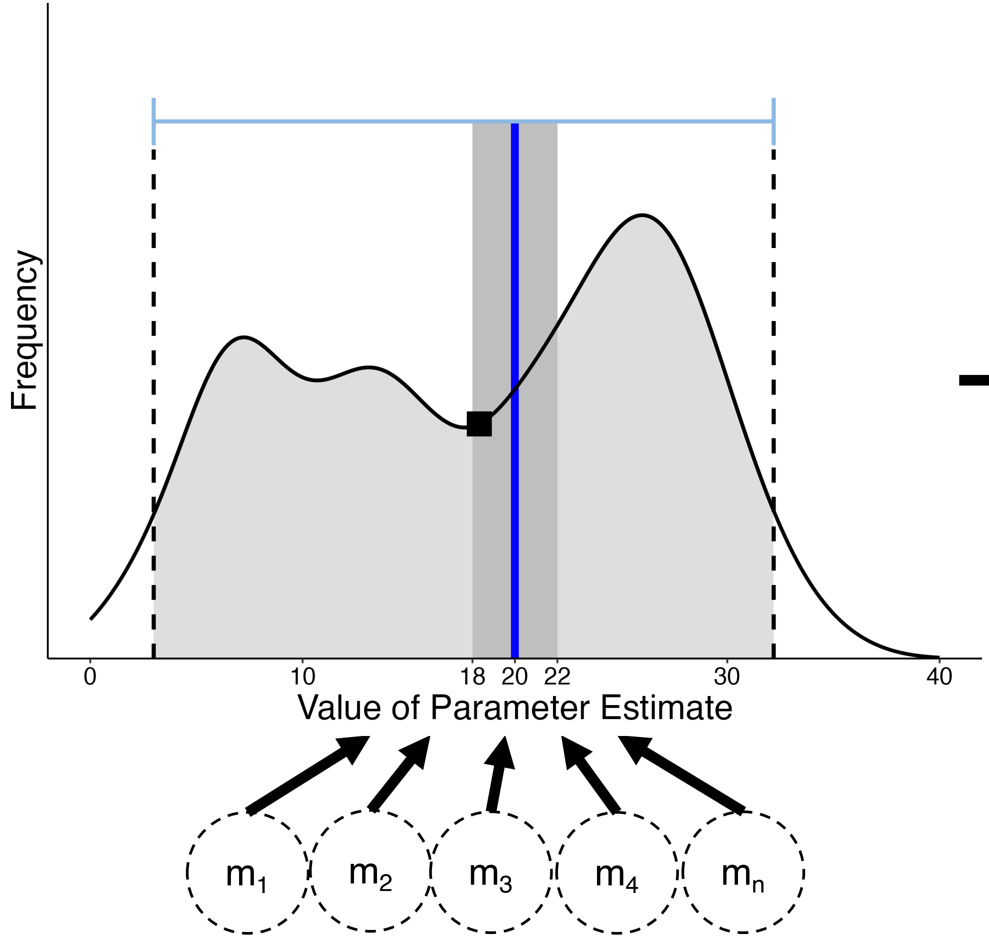
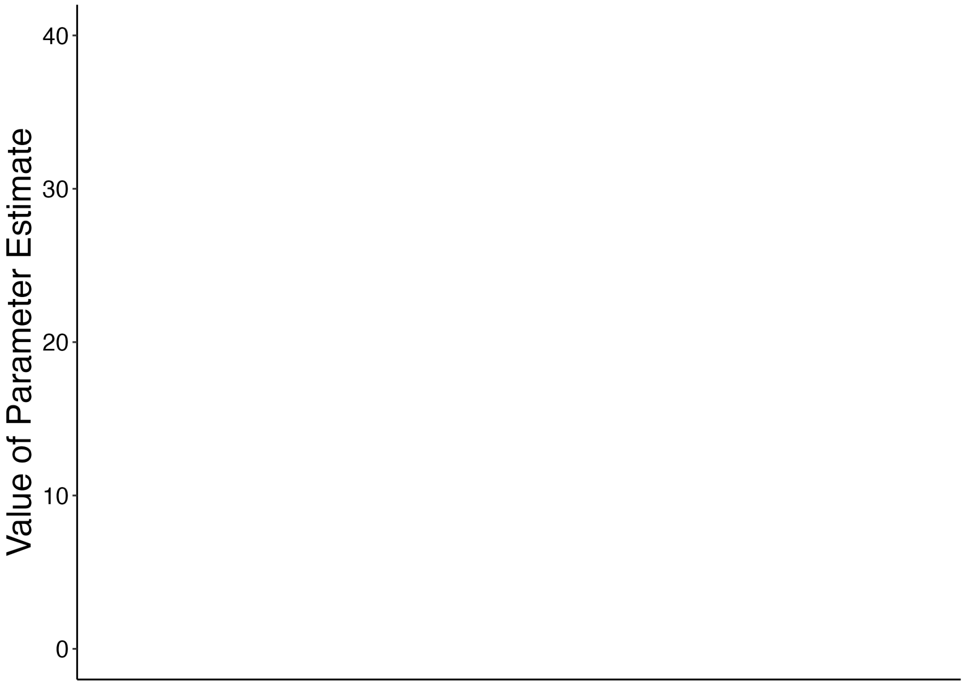
Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Delta Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



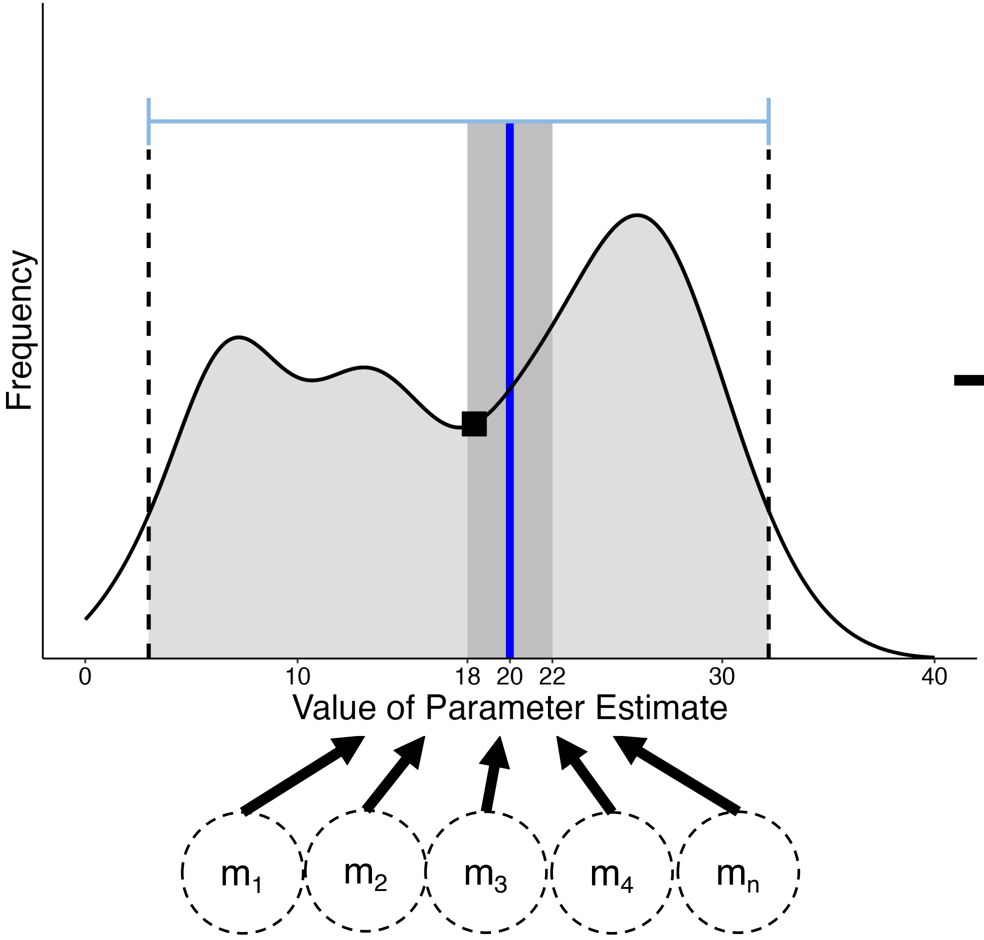
n = 1000

Bias/Precision Plot for Fixed-Effect Triquarter-Halfway Delta Parameter



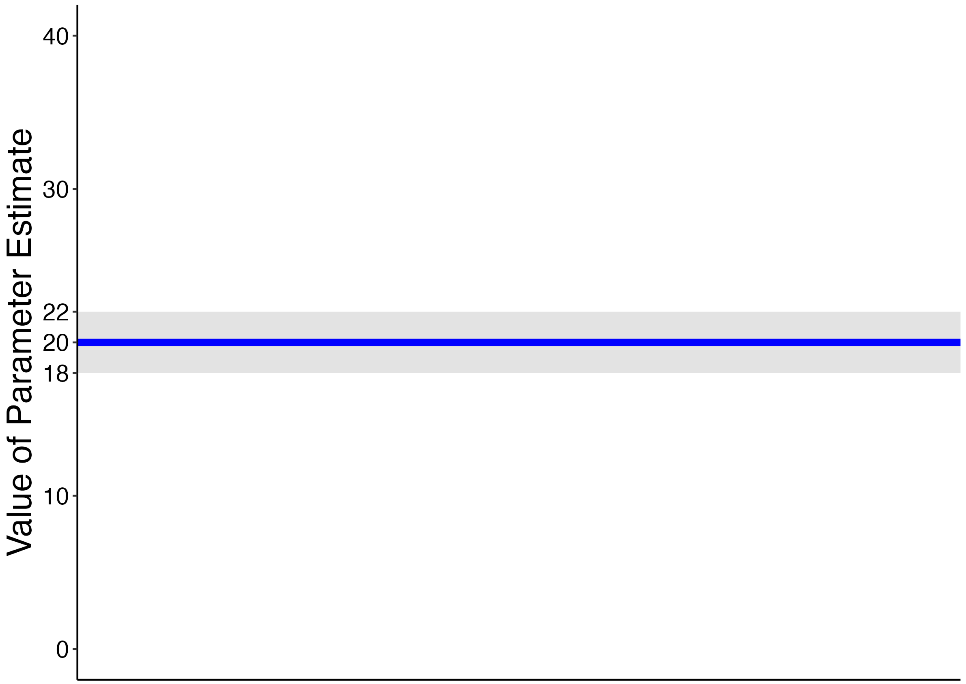
Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Delta Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



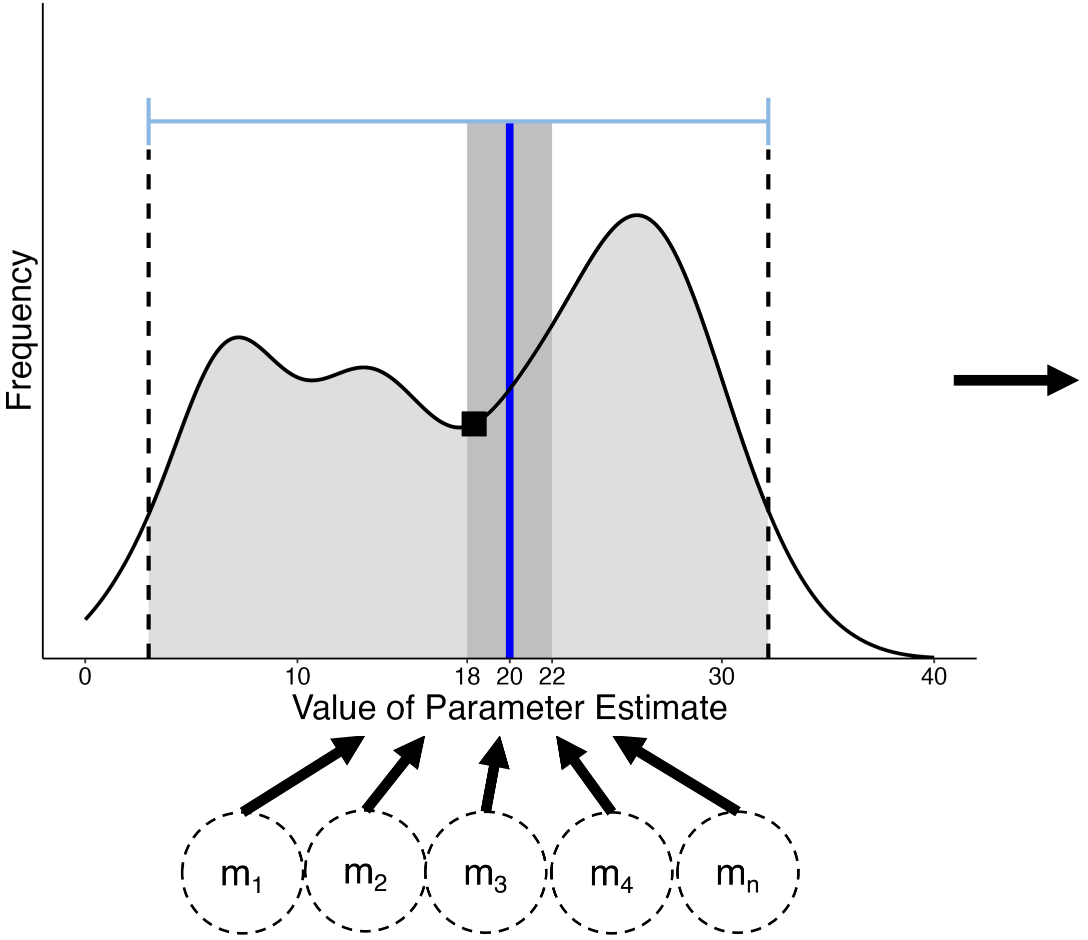
n = 1000

Bias/Precision Plot for Fixed-Effect Triquarter-Halfway Delta Parameter



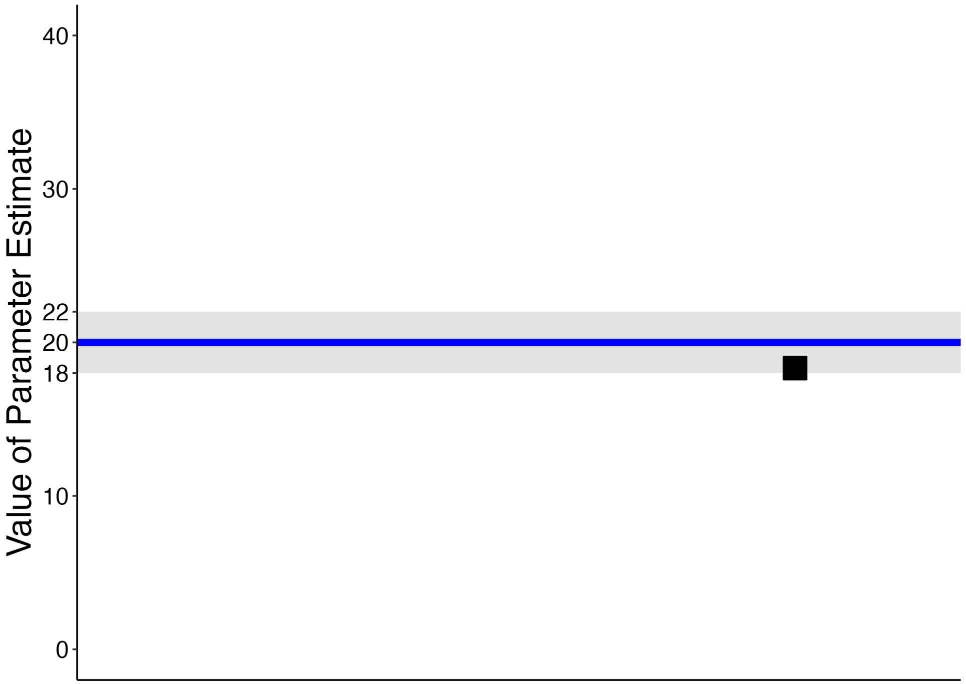
Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Delta Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



n = 1000

Bias/Precision Plot for Fixed-Effect Triquarter-Halfway Delta Parameter



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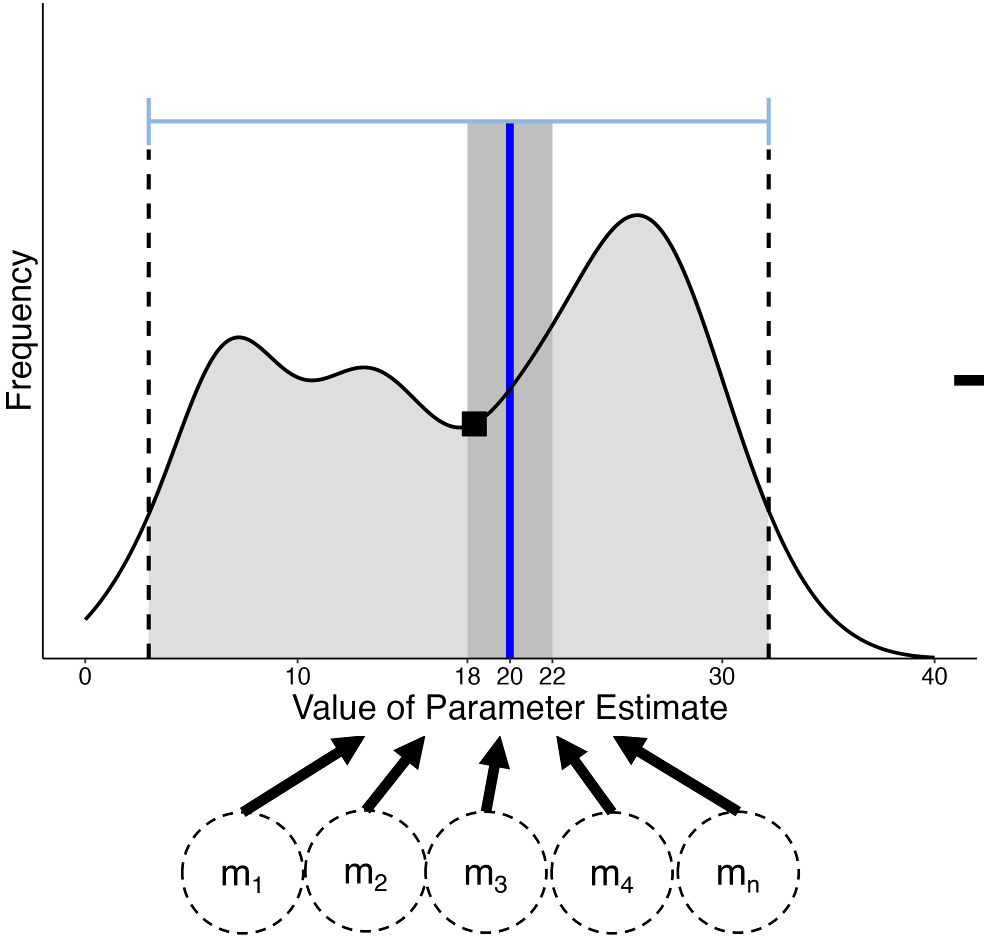
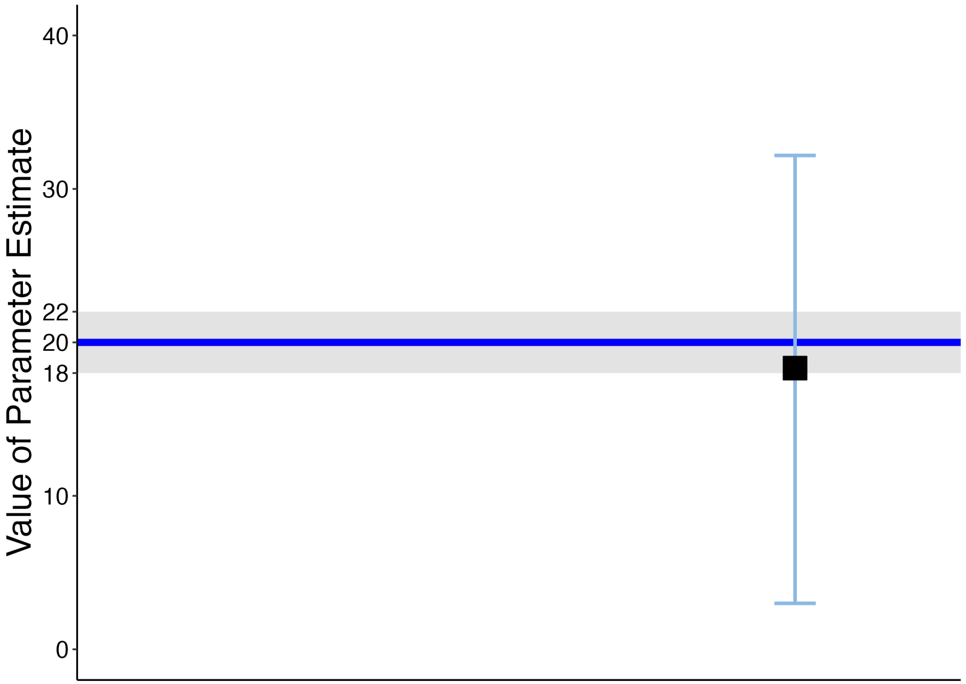
Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Delta Parameter (γ_{fixed}; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



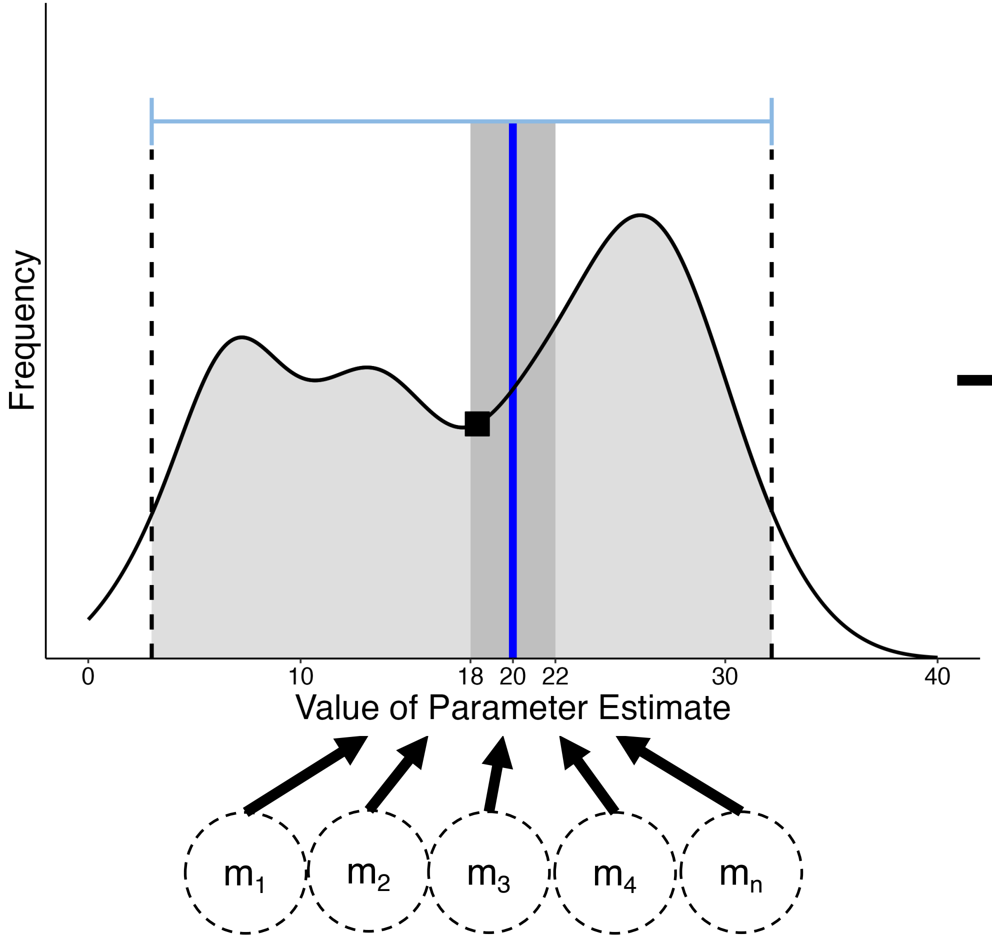
n = 1000

Bias/Precision Plot for Fixed-Effect Triquarter-Halfway Delta Parameter



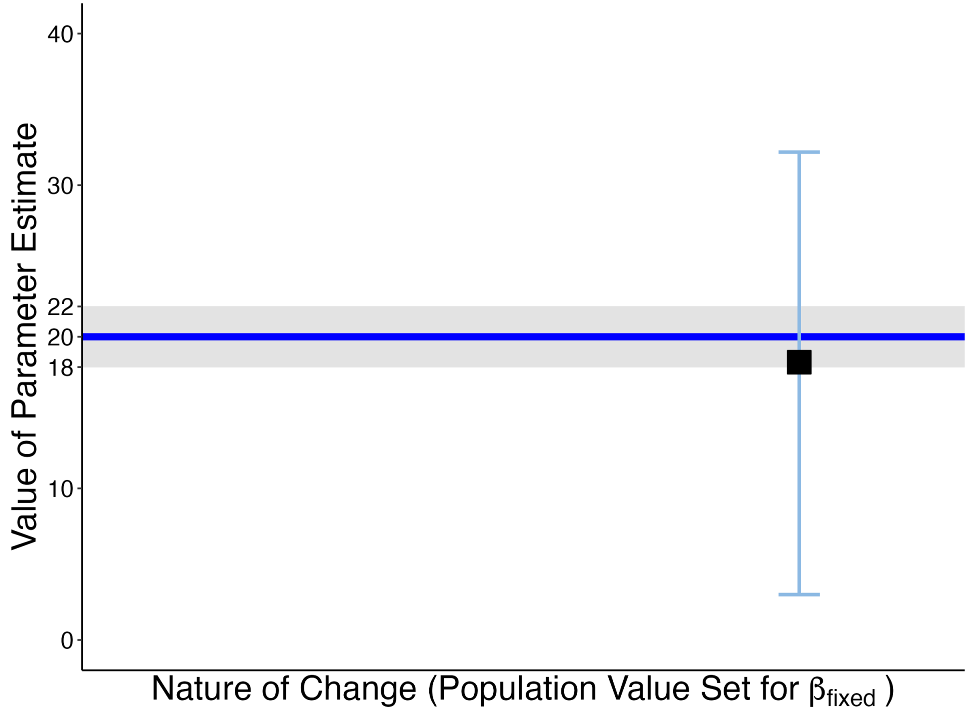
Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Delta Parameter (γ_{fixed}; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



n = 1000

Bias/Precision Plot for Fixed-Effect Triquarter-Halfway Delta Parameter



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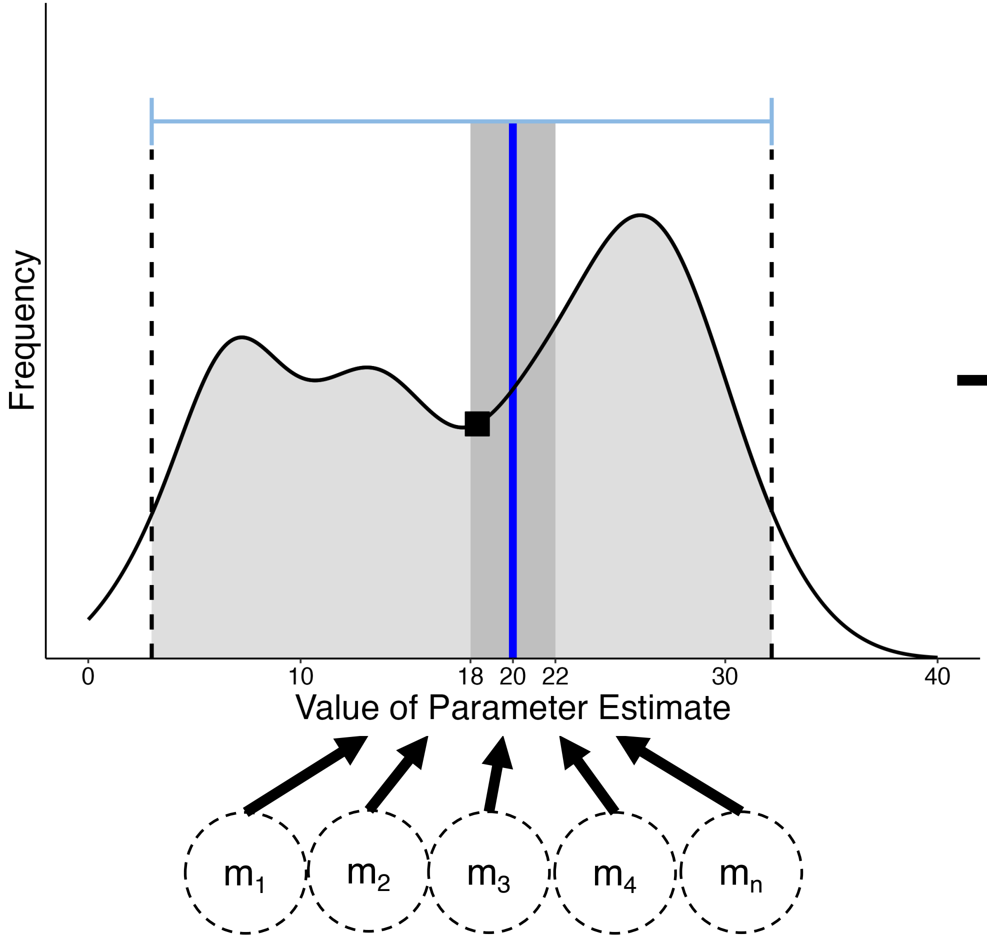
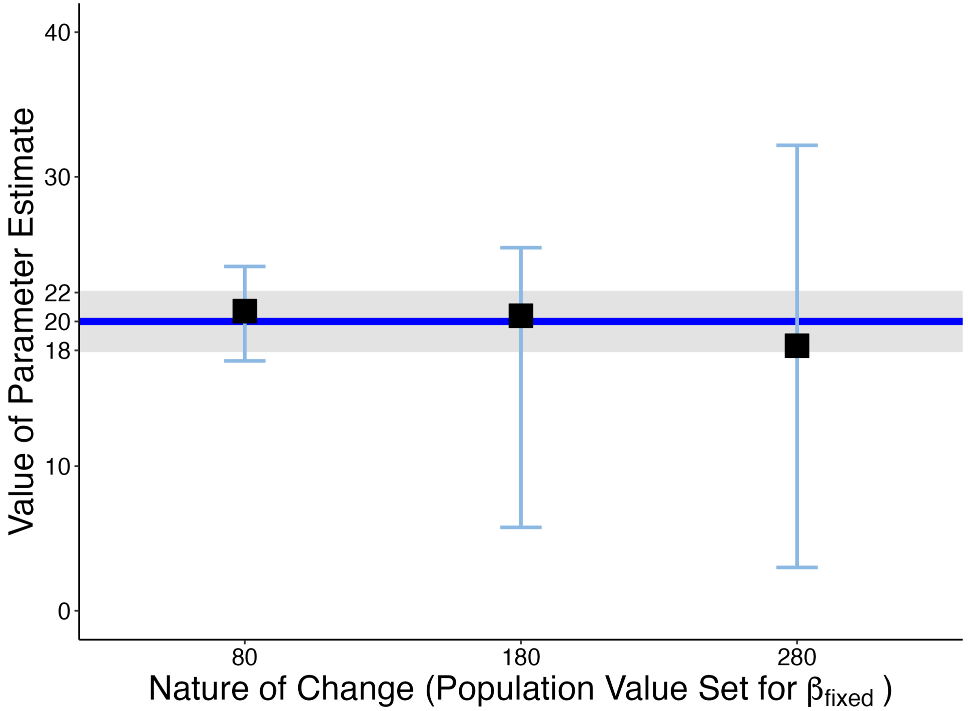
Values Estimated for Fixed-Effect Triquarter-Halfway Delta Parameter (γ_{fixed}; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



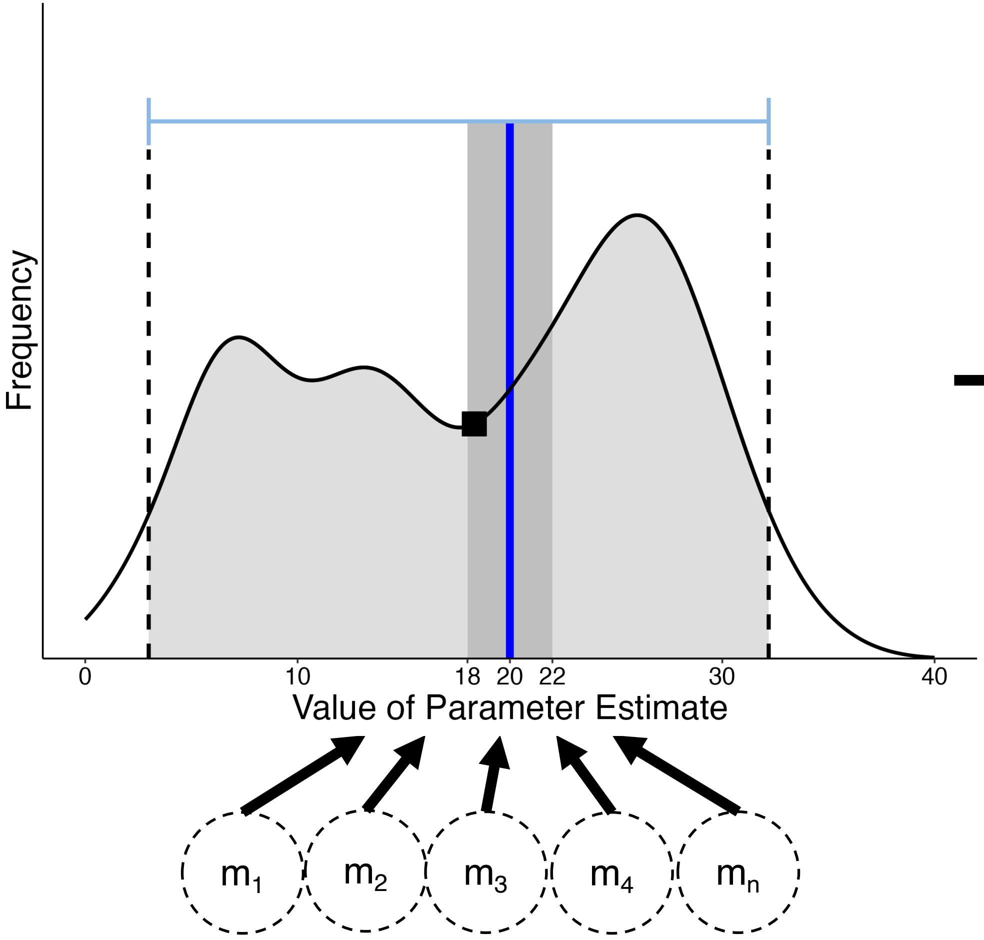
n = 1000

Bias/Precision Plot for Fixed-Effect Triquarter-Halfway Delta Parameter



Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Delta Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



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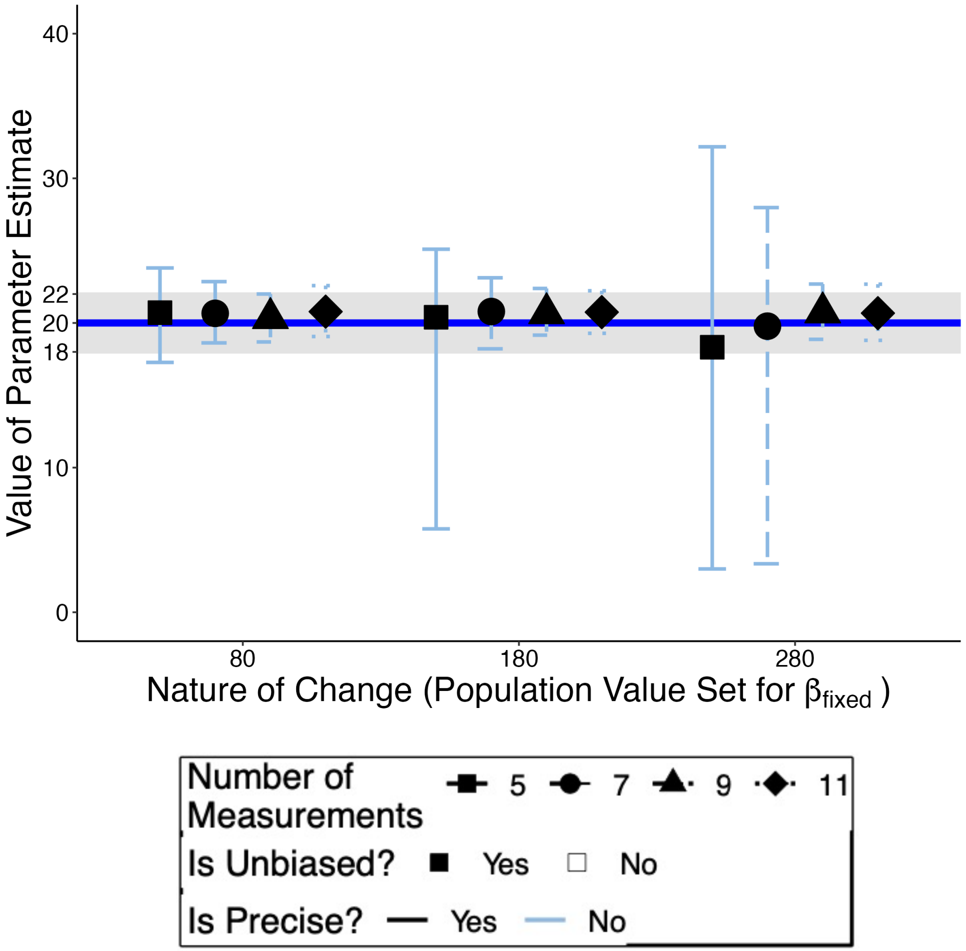
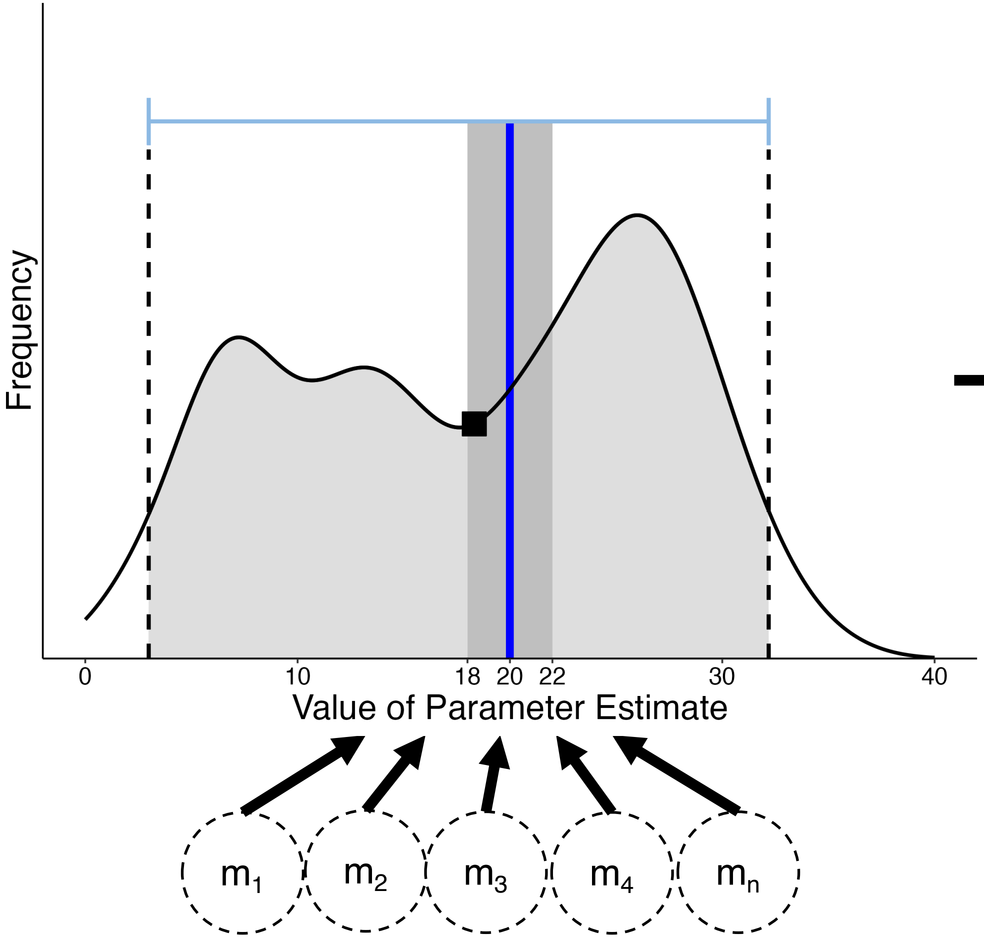
Bias/Precision Plot for Fixed-Effect Triquarter-Halfway Delta Parameter



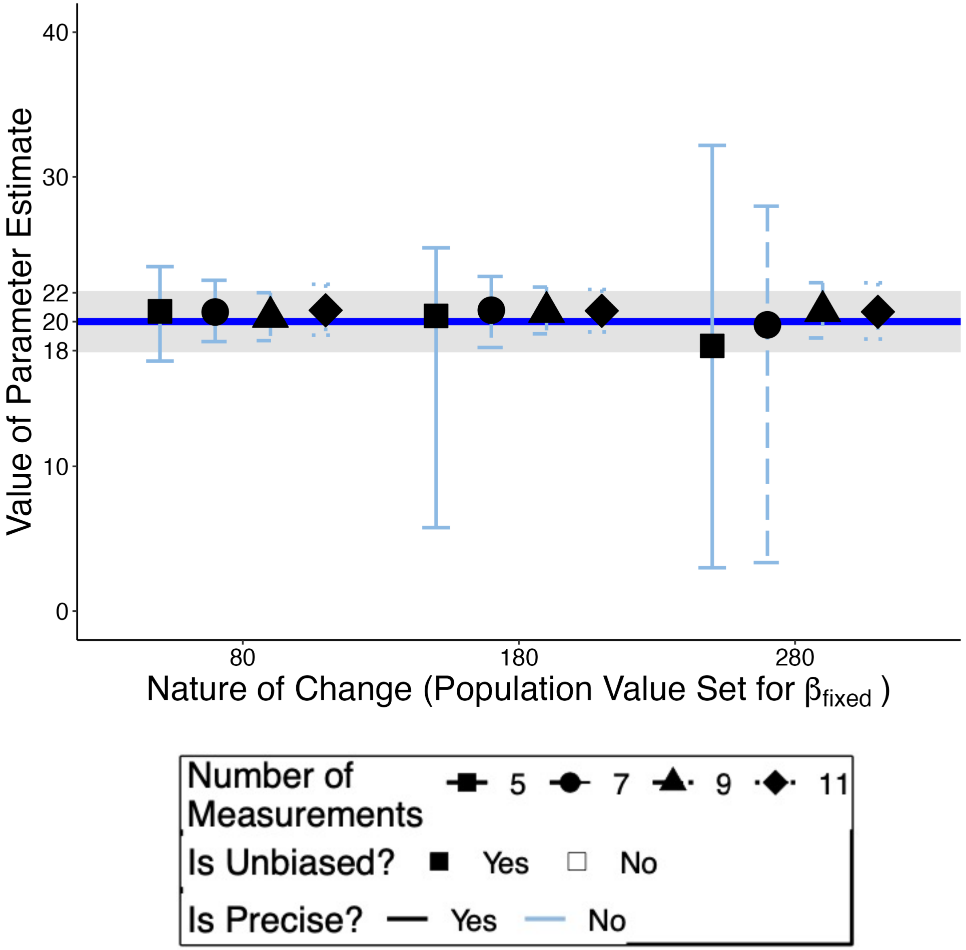
Monte Carlo method: Model performance

Values Estimated for Fixed-Effect Triquarter-Halfway Delta Parameter (γ_{fixed} ; β_{fixed} = 180.00, NM = 5, Spacing = Time-Interval Increasing)



n = 1000

Bias/Precision Plot for Fixed-Effect Triquarter-Halfway Delta Parameter for Time-Interval Increasing Spacing



Parameter Values Estimated for Day- and Likert-Unit Parameters in Experiment 1

Measurement Spacing	Number of Measurements	β_{fixed} (Days to halfway elevation)			β_{random} (Days to halfway elevation) Pop value = 10.00			γ_{fixed} (Triquarter-halfway delta) Pop value = 20.00			γ_{random} (Triquarter-halfway delta) Pop value = 4.00		
		80	180	280	80	180	280	80	180	280	80	180	280
Equal spacing	5	79.73	179.78	279.81□	10.14	10.40	10.08	19.37	19.49	19.71	7.41□	14.53□	8.11□
	7	80.21	178.99	279.55□	10.16	10.55	10.13	20.67	20.83	20.60	4.37	5.14□	4.41□
	9	80.00	179.94	279.99□	10.29	10.37	10.34	20.77	20.76	20.67	4.24	4.14	4.30
	11	80.03	180.01	279.88□	10.27	10.29	10.32	20.64	20.70	20.64	4.13	4.08	4.18
Time-interval increasing	5	79.88	180.10	274.37□	10.32	9.73	13.04□	20.71	20.39	18.32	4.57□	4.99□	6.20□
	7	80.19	179.82	279.86□	10.42	10.47	10.14	20.66	20.79	19.78	4.29	4.87□	7.03□
	9	79.59	179.06	279.70□	10.07	10.22	10.20	20.33	20.66	20.72	4.17	4.25	4.32
	11	79.89	179.84	279.62□	10.38	10.30	10.47	20.78	20.75	20.68	4.23	4.18	4.13
Time-interval decreasing	5	70.67	179.92	279.63□	15.28□	9.80	10.22	16.63	20.07	20.55	5.48□	5.17□	4.59□
	7	78.23	178.22	279.84□	10.08	10.46	10.39	19.38	20.59	20.69	6.80□	5.09□	4.24
	9	79.95	179.34	278.98□	10.03	10.20	10.05	20.42	20.54	20.28	4.37	4.32	4.19
	11	79.42	179.70	279.52□	10.38	10.13	10.06	20.75	20.45	20.31	4.17	4.16	4.17
Middle-and-extreme spacing	5	71.95	179.61	287.73□	16.78□	10.26	16.74□	15.59	20.61	17.09	6.54□	4.24	8.61□
	7	80.45	180.00	279.15□	13.93□	10.25	13.69□	20.71	20.58	20.61	5.21□	4.16	4.98□
	9	80.28	180.05	279.63□	10.42	10.24	10.24	20.91	20.65	20.85	4.74□	4.26	4.72□
	11	80.19	179.96	279.86□	10.27	10.28	10.15	20.71	20.70	20.71	4.14	4.08	4.16

Experiment 1 design (Monte Carlo method)

= model

= sample

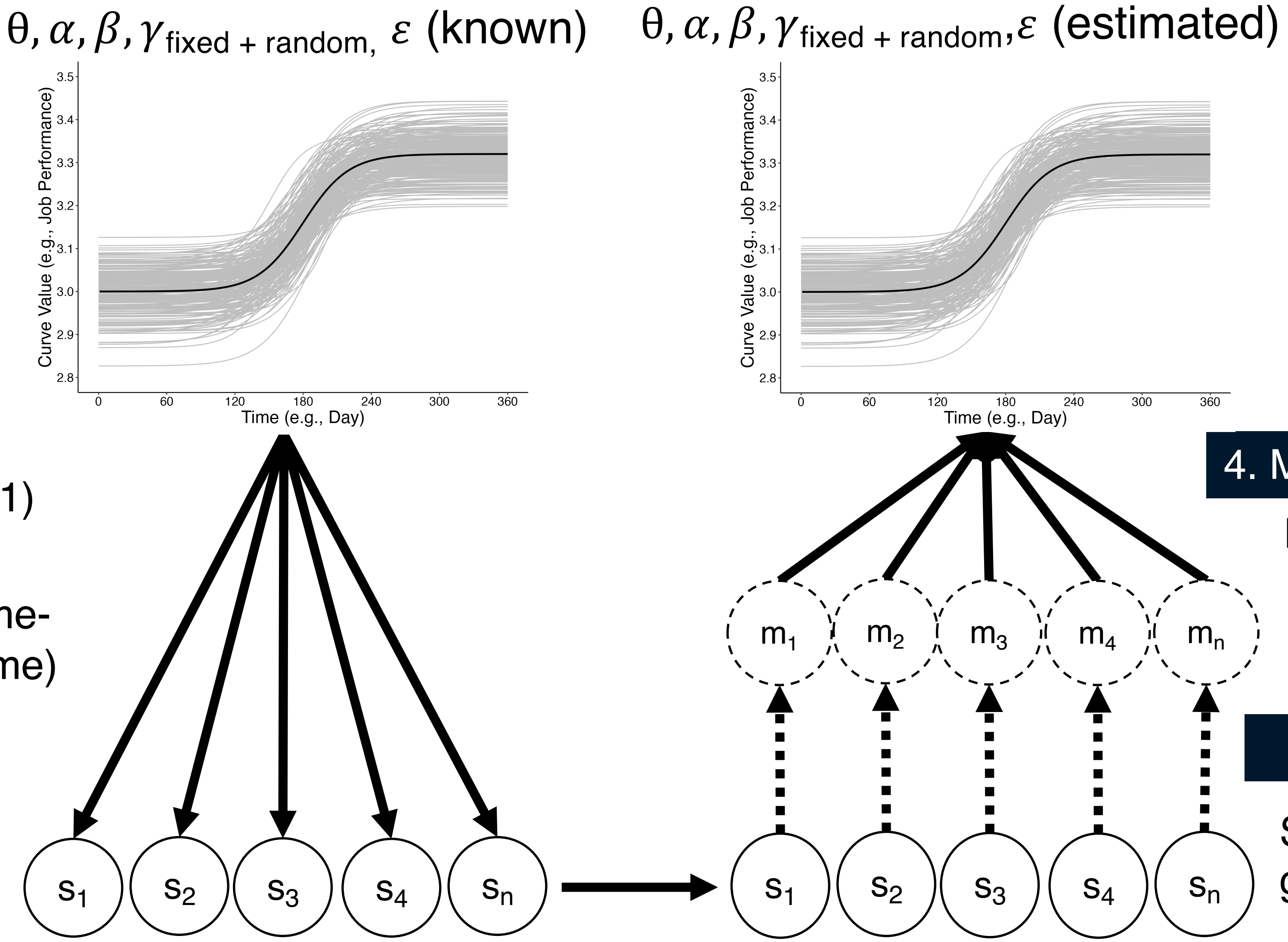
1. Population definition

IV 1: Nature of change (β_{fixed} = 80, 180, 280)

2. Sample generation

IV 2: Number of measurements (5, 7, 9, 11)

IV 3: Spacing of measurements (equal, time-inc., time dec., mid-extreme)



n = k = 1000

4. Model performance

Bias + precision

3. Modelling

Structured latent growth model

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Question 1: Does placing measurements near periods of change increase model performance?

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Answer 1: Model performance increases when measurements are placed near periods of change

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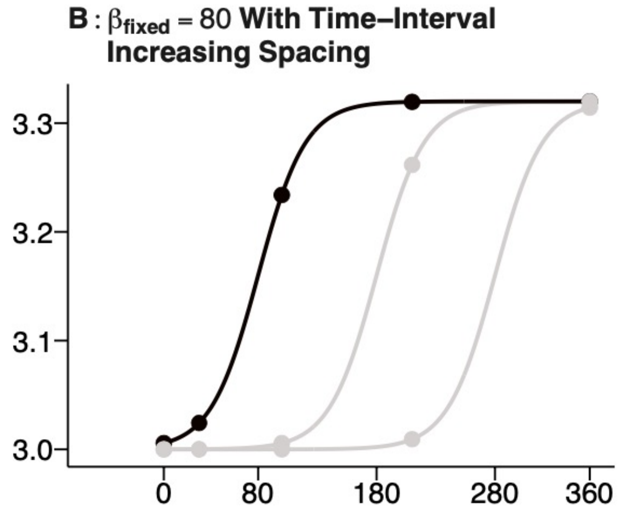
Answer 1: Model performance increases when measurements are placed near periods of change



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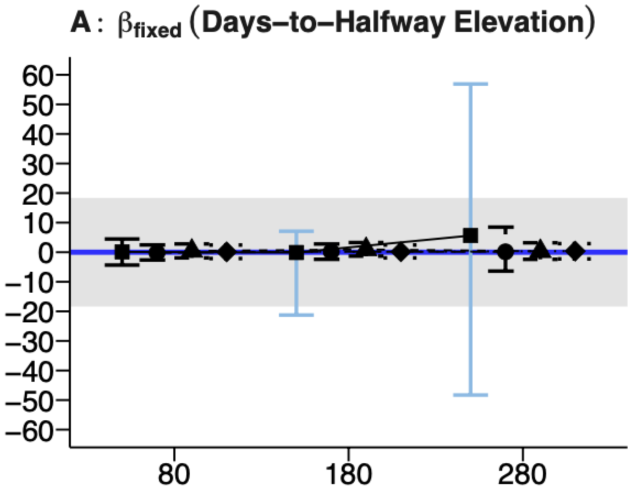
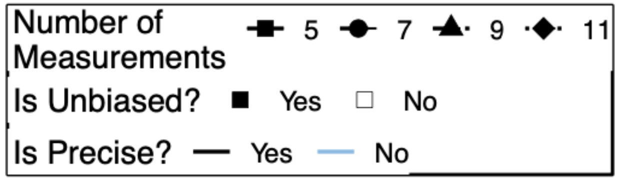
Answer 1: Model performance increases when measurements are placed near periods of change

Time-interval increasing spacing





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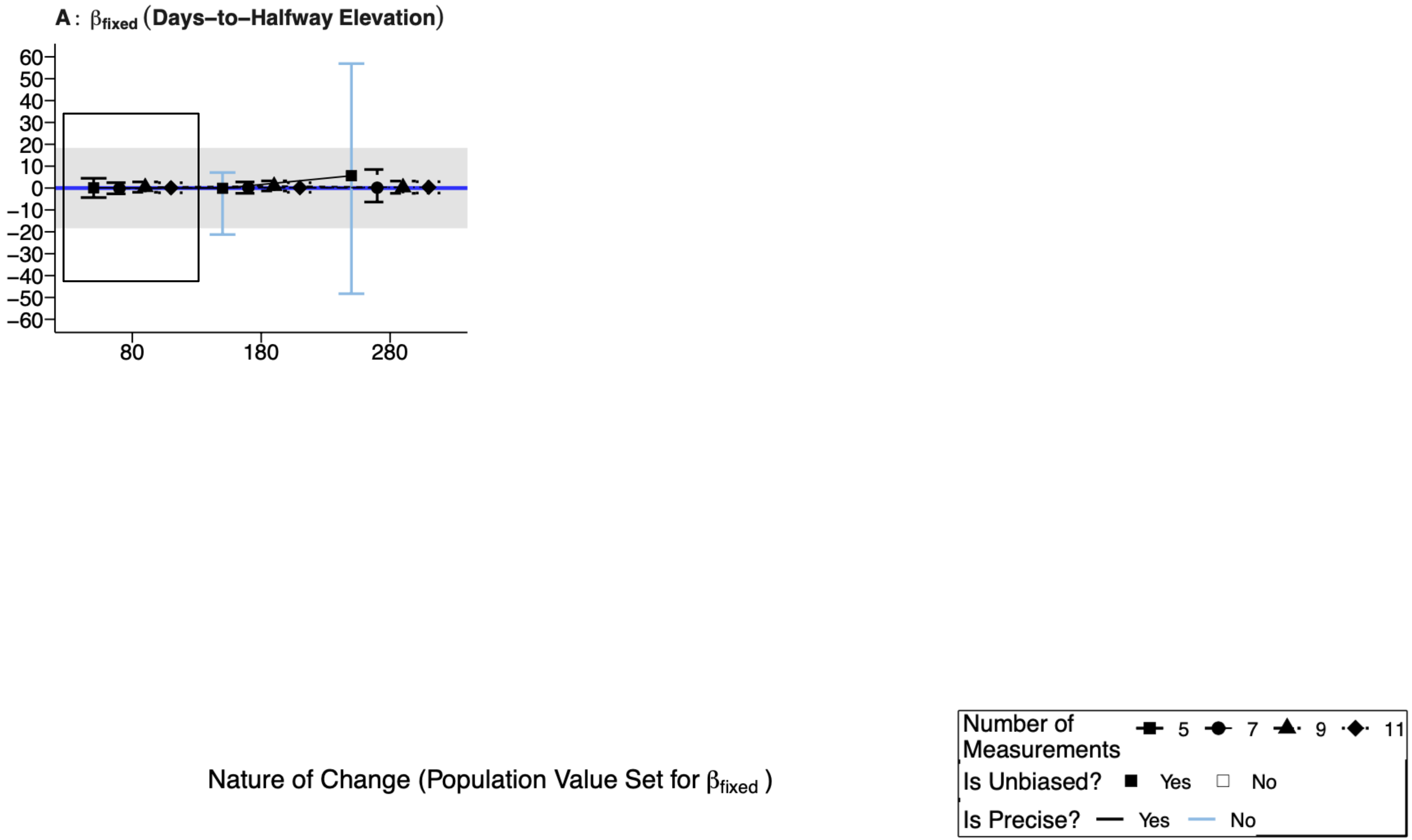

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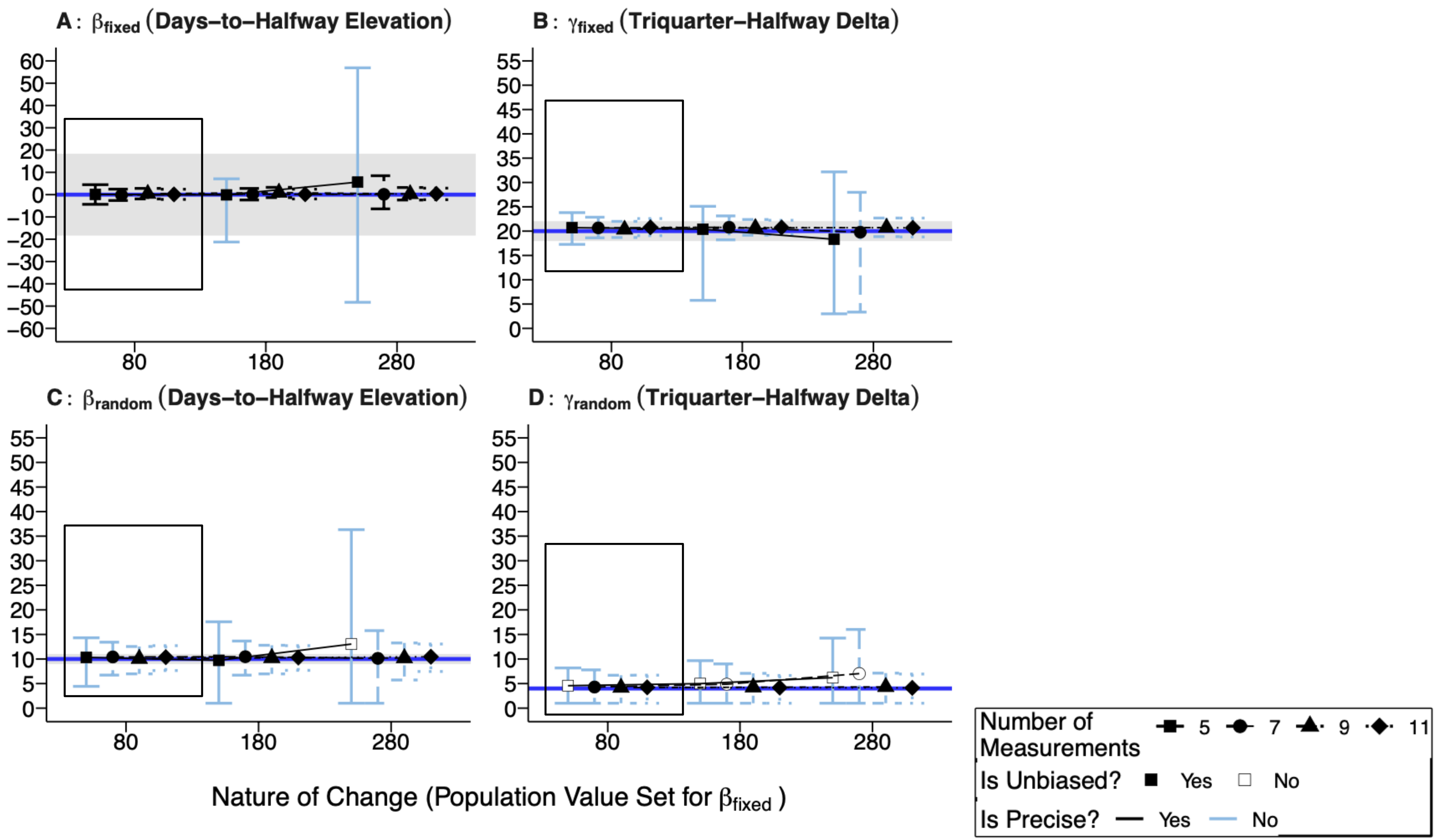
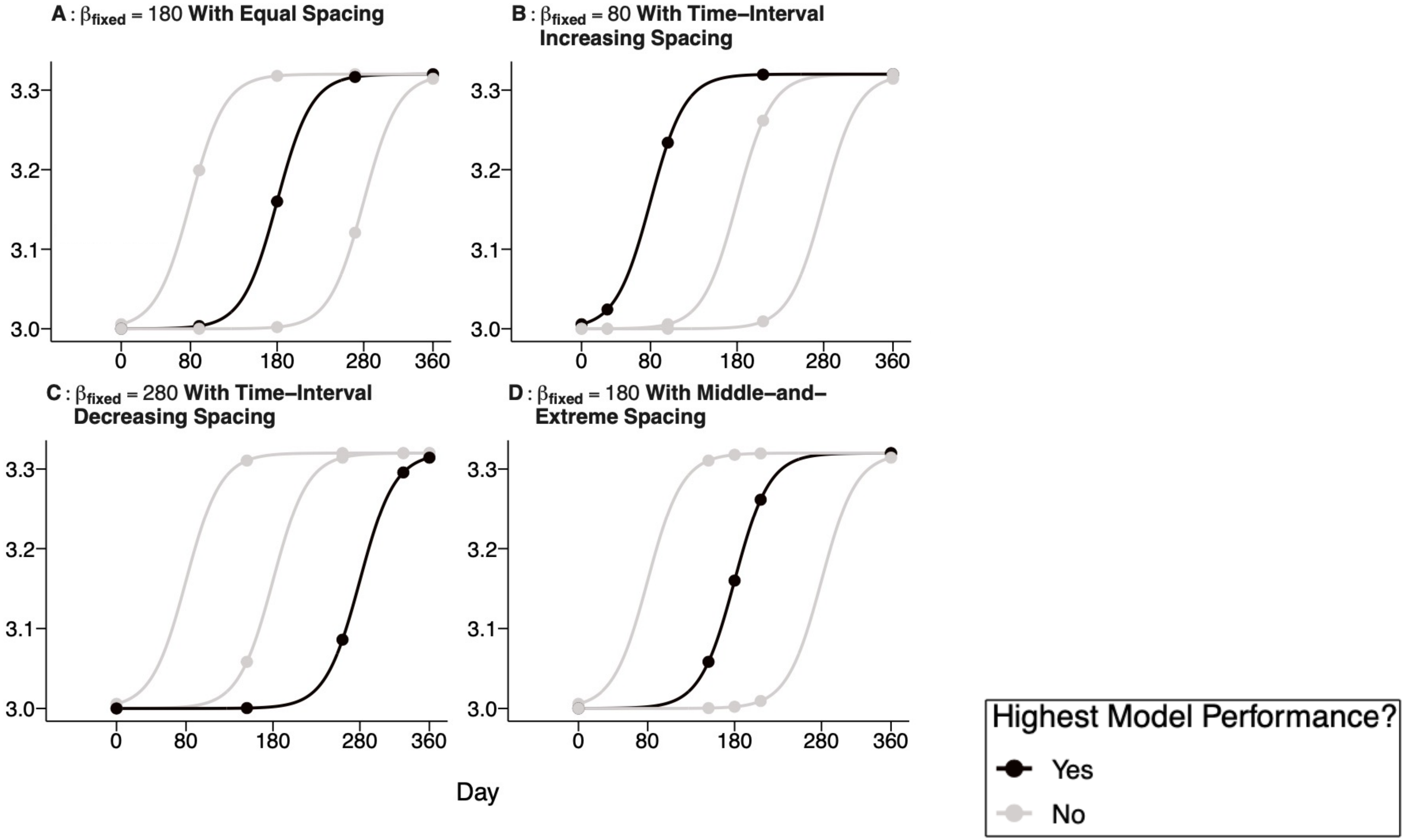
Time-interval increasing spacing



Answer 1: Model performance increases when measurements are placed near periods of change



Question 1: Does placing measurements near periods of change increase model performance?

Answer 1: Model performance increases when measurements are placed near periods of change

Question 2: How to space measurements when the nature of change is unknown?

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Question 1: Does placing measurements near periods of change increase model performance?

Answer 1: Model performance increases when measurements are placed near periods of change

Question 2: How to space measurements when the nature of change is unknown?

Answer 2: When the nature of change is unknown, model performance is highest with equal spacing

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Answer 2: When the nature of change is unknown, model performance is highest with equal spacing

Spacing Schedule	Qualitative Description
Equal (see Figure 2.5 and Table 2.3)	
Time-interval increasing (see Figure 2.7 and Table 2.6)	
Time-interval decreasing (see Figure 2.9 and Table 2.9)	
Middle-and-extreme (see Figure 2.11 and Table 2.9)	

Answer 2: When the nature of change is unknown, model performance is highest with equal spacing

Spacing Schedule	Qualitative Description
Equal (see Figure 2.5 and Table 2.3)	Largest improvements in bias and precision with NM = 7
Time-interval increasing (see Figure 2.7 and Table 2.6)	
Time-interval decreasing (see Figure 2.9 and Table 2.9)	
Middle-and-extreme (see Figure 2.11 and Table 2.9)	

Answer 2: When the nature of change is unknown, model performance is highest with equal spacing

Spacing Schedule	Qualitative Description
Equal (see Figure 2.5 and Table 2.3)	Largest improvements in bias and precision with NM = 7
Time-interval increasing (see Figure 2.7 and Table 2.6)	Largest improvements in bias and precision with NM = 9
Time-interval decreasing (see Figure 2.9 and Table 2.9)	Largest improvements in bias and precision with NM = 9
Middle-and-extreme (see Figure 2.11 and Table 2.9)	Largest improvements in bias and precision with NM = 9

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Answer 2: When the nature of change is unknown, model performance is highest with equal spacing

Spacing Schedule	Qualitative Description	Error Bar Summary
Equal (see Figure 2.5 and Table 2.3)	Largest improvements in bias and precision with NM = 7	
Time-interval increasing (see Figure 2.7 and Table 2.6)	Largest improvements in bias and precision with NM = 9	
Time-interval decreasing (see Figure 2.9 and Table 2.9)	Largest improvements in bias and precision with NM = 9	
Middle-and-extreme (see Figure 2.11 and Table 2.9)	Largest improvements in bias and precision with NM = 9	

Answer 2: When the nature of change is unknown, model performance is highest with equal spacing

Spacing Schedule	Qualitative Description	Error Bar Summary β_{fixed}
Equal (see Figure 2.5 and Table 2.3)	Largest improvements in bias and precision with NM = 7	5.64
Time-interval increasing (see Figure 2.7 and Table 2.6)	Largest improvements in bias and precision with NM = 9	4.97
Time-interval decreasing (see Figure 2.9 and Table 2.9)	Largest improvements in bias and precision with NM = 9	4.88
Middle-and-extreme (see Figure 2.11 and Table 2.9)	Largest improvements in bias and precision with NM = 9	6.51

Answer 2: When the nature of change is unknown, model performance is highest with equal spacing

		Error Bar Summary	
Spacing Schedule	Qualitative Description	β_{fixed}	γ_{fixed}
Equal (see Figure 2.5 and Table 2.3)	Largest improvements in bias and precision with NM = 7	5.64	4.37
Time-interval increasing (see Figure 2.7 and Table 2.6)	Largest improvements in bias and precision with NM = 9	4.97	3.45
Time-interval decreasing (see Figure 2.9 and Table 2.9)	Largest improvements in bias and precision with NM = 9	4.88	3.40
Middle-and-extreme (see Figure 2.11 and Table 2.9)	Largest improvements in bias and precision with NM = 9	6.51	5.55

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Answer 2: When the nature of change is unknown, model performance is highest with equal spacing

Spacing Schedule	Qualitative Description	Error Bar Summary		
		β_{fixed}	γ_{fixed}	β_{random}
Equal (see Figure 2.5 and Table 2.3)	Largest improvements in bias and precision with NM = 7	5.64	4.37	7.74
Time-interval increasing (see Figure 2.7 and Table 2.6)	Largest improvements in bias and precision with NM = 9	4.97	3.45	6.31
Time-interval decreasing (see Figure 2.9 and Table 2.9)	Largest improvements in bias and precision with NM = 9	4.88	3.40	6.15
Middle-and-extreme (see Figure 2.11 and Table 2.9)	Largest improvements in bias and precision with NM = 9	6.51	5.55	9.02

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Answer 2: When the nature of change is unknown, model performance is highest with equal spacing

		Error Bar Summary			
Spacing Schedule	Qualitative Description	β_{fixed}	γ_{fixed}	β_{random}	γ_{random}
Equal (see Figure 2.5 and Table 2.3)	Largest improvements in bias and precision with NM = 7	5.64	4.37	7.74	7.02
Time-interval increasing (see Figure 2.7 and Table 2.6)	Largest improvements in bias and precision with NM = 9	4.97	3.45	6.31	5.97
Time-interval decreasing (see Figure 2.9 and Table 2.9)	Largest improvements in bias and precision with NM = 9	4.88	3.40	6.15	5.96
Middle-and-extreme (see Figure 2.11 and Table 2.9)	Largest improvements in bias and precision with NM = 9	6.51	5.55	9.02	7.20

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Question 1: Does placing measurements near periods of change increase model performance?

Answer 1: Model performance increases when measurements are placed near periods of change

Question 2: How to space measurements when the nature of change is unknown?

Answer 2: When the nature of change is unknown, model performance is highest with equal spacing

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Experiment 2

Question: For each spacing schedule, what combination of measurement number and sample size is needed to obtain high model performance (i.e., low bias, high precision)?

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Experiment 2 – Systematic Review

Number of measurements

Spacing of measurements

Experiment 2 – Systematic Review

Number of measurements

Spacing of measurements

Sample size

Experiment 2 – Systematic Review

Number of measurements

Spacing of measurements

Sample size

Few guidelines

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Effect	Nonlinear pattern
Main effects	
Number of measurements (NM)	6 studies
Spacing of measurements (SM)	1 study
Sample size (S)	7 studies

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Effect	Nonlinear pattern
Main effects	
Number of measurements (NM)	6 studies
Spacing of measurements (SM)	1 study
Sample size (S)	7 studies
Two-way interactions	
NM x SM	1 study
NM x S	5 studies
SM x S	**Cell 5 (Exp. 2)**
TS x S	2 studies

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Effect	Nonlinear pattern
Main effects	
Number of measurements (NM)	6 studies
Spacing of measurements (SM)	1 study
Sample size (S)	7 studies
Two-way interactions	
NM x SM	1 study
NM x S	5 studies
SM x S	**Cell 5 (Exp. 2)**
TS x S	2 studies
Three-way interactions	
NM x SM x S	**Cell 9 (Exp. 2)**

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Effect	Nonlinear pattern
Main effects	
Number of measurements (NM)	6 studies
Spacing of measurements (SM)	1 study
Sample size (S)	7 studies
Two-way interactions	
NM x SM	1 study
NM x S	5 studies
SM x S	**Cell 5 (Exp. 2)**
TS x S	2 studies
Three-way interactions	
NM x SM x S	**Cell 9 (Exp. 2)**

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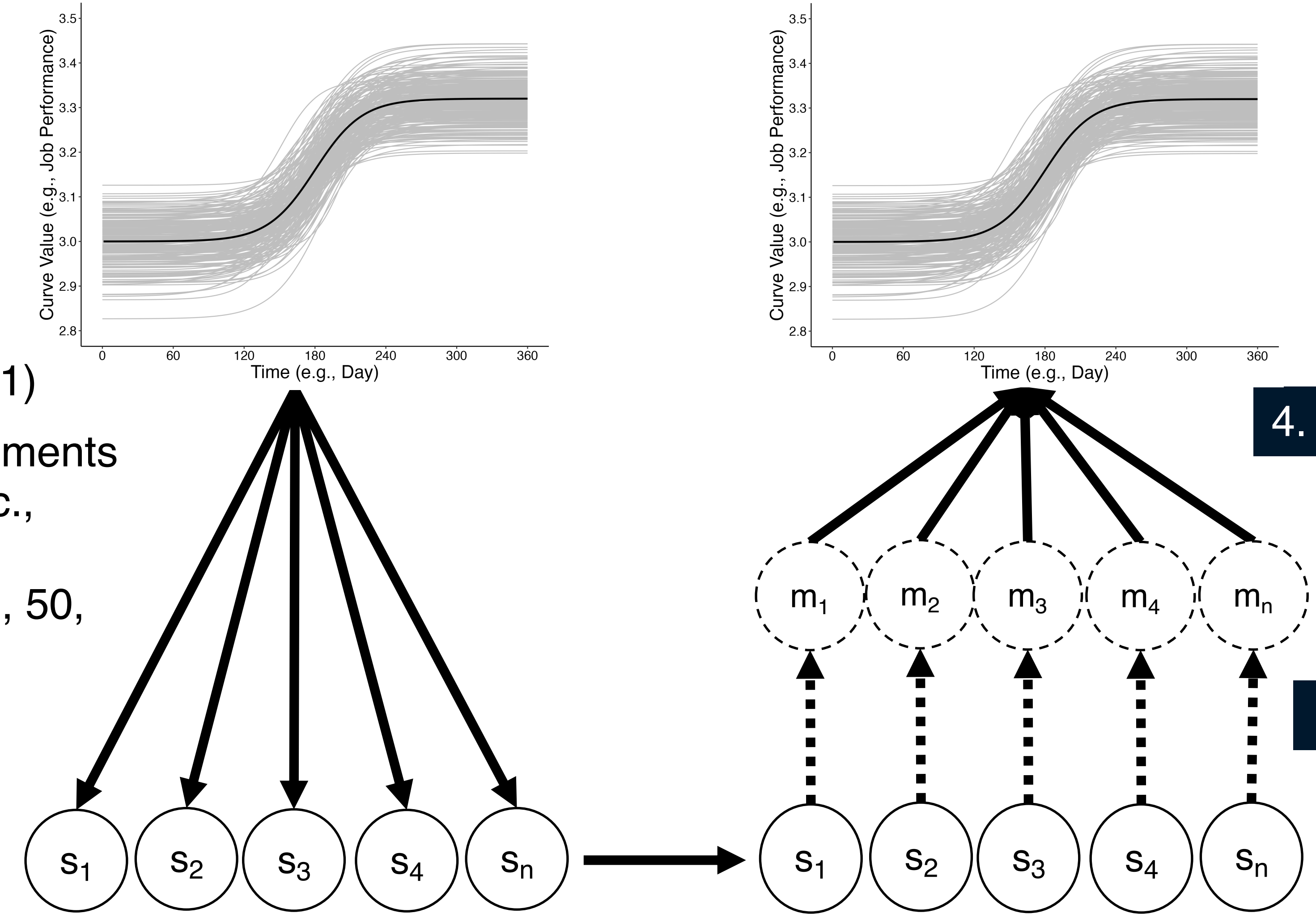
Experiment 2 design (Monte Carlo method)

= model
= sample

1. Population definition

$\theta, \alpha, \beta, \gamma_{\text{fixed + random}}, \varepsilon$ (known)

$\theta, \alpha, \beta, \gamma_{\text{fixed + random}}, \varepsilon$ (estimated)



2. Sample generation

IV 1: Number of measurements (5, 7, 9, 11)

IV 2: Spacing of measurements (equal, time-inc., time dec., middle-extreme)

IV 3: Sample size (N = 30, 50, 100, 200, 500, 1000)

$n = k = 1000$

4. Model performance

Bias + precision

3. Modelling

Structured latent growth model

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Experiment 2

Question: For each spacing schedule, what combination of measurement number and sample size is needed to obtain high model performance (i.e., low bias, high precision)?

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Experiment 2

Question: For each spacing schedule, what combination of measurement number and sample size is needed to obtain high model performance (i.e., low bias, high precision)?

Answer: The greatest improvements in model performance for each spacing schedule result from either seven measurements with $N \geq 200$ or nine measurements with $N \leq 100$.

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Answer: The greatest improvements in model performance for each spacing schedule result from either seven measurements with $N \geq 200$ or nine measurements with $N \leq 100$.

Spacing Schedule	Qualitative Description
Equal (see Figure 3.2 and Table 3.1)	
Time-interval increasing (see Figure 3.3 and Table 3.3)	
Time-interval decreasing (see Figure 3.4 and Table 3.5)	

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Answer: The greatest improvements in model performance for each spacing schedule result from either seven measurements with $N \geq 200$ or nine measurements with $N \leq 100$.

Spacing Schedule	Qualitative Description
Equal (see Figure 3.2 and Table 3.1)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$
Time-interval increasing (see Figure 3.3 and Table 3.3)	
Time-interval decreasing (see Figure 3.4 and Table 3.5)	

Answer: The greatest improvements in model performance for each spacing schedule result from either seven measurements with $N \geq$ 200 or nine measurements with $N \leq$100.

Spacing Schedule	Qualitative Description
Equal (see Figure 3.2 and Table 3.1)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$
Time-interval increasing (see Figure 3.3 and Table 3.3)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$
Time-interval decreasing (see Figure 3.4 and Table 3.5)	

Answer: The greatest improvements in model performance for each spacing schedule result from either seven measurements with $N \geq 200$ or nine measurements with $N \leq 100$.

Spacing Schedule	Qualitative Description
Equal (see Figure 3.2 and Table 3.1)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$
Time-interval increasing (see Figure 3.3 and Table 3.3)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$
Time-interval decreasing (see Figure 3.4 and Table 3.5)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$

Answer: The greatest improvements in model performance for each spacing schedule result from either seven measurements with $N \geq$ 200 or nine measurements with $N \leq$100.

		Error Bar Summary
Spacing Schedule	Qualitative Description	β_{fixed}
Equal (see Figure 3.2 and Table 3.1)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	12.67
Time-interval increasing (see Figure 3.3 and Table 3.3)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	13.27
Time-interval decreasing (see Figure 3.4 and Table 3.5)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	13.41

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Answer: The greatest improvements in model performance for each spacing schedule result from either seven measurements with $N \geq$ 200 or nine measurements with $N \leq$100.

		Error Bar Summary	
Spacing Schedule	Qualitative Description	β_{fixed}	γ_{fixed}
Equal (see Figure 3.2 and Table 3.1)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	12.67	9.79
Time-interval increasing (see Figure 3.3 and Table 3.3)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	13.27	9.69
Time-interval decreasing (see Figure 3.4 and Table 3.5)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	13.41	9.62

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Answer: The greatest improvements in model performance for each spacing schedule result from either seven measurements with $N \geq$ 200 or nine measurements with $N \leq$100.

Spacing Schedule	Qualitative Description	Error Bar Summary		
		β_{fixed}	γ_{fixed}	β_{random}
Equal (see Figure 3.2 and Table 3.1)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	12.67	9.79	16.02
Time-interval increasing (see Figure 3.3 and Table 3.3)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	13.27	9.69	16.28
Time-interval decreasing (see Figure 3.4 and Table 3.5)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	13.41	9.62	16.16

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Answer: The greatest improvements in model performance for each spacing schedule result from either seven measurements with $N \geq$ 200 or nine measurements with $N \leq 100$.

		Error Bar Summary			
Spacing Schedule	Qualitative Description	β_{fixed}	γ_{fixed}	β_{random}	γ_{random}
Equal (see Figure 3.2 and Table 3.1)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	12.67	9.79	16.02	10.08
Time-interval increasing (see Figure 3.3 and Table 3.3)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	13.27	9.69	16.28	10.15
Time-interval decreasing (see Figure 3.4 and Table 3.5)	Largest improvements in bias and precision using NM = 7 with $N \geq 200$ or NM = 9 with $N \leq 100$	13.41	9.62	16.16	10.32

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Experiment 3

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Experiment 3

Question: Do the number of measurements and sample sizes needed to obtain high model performance (i.e., low bias, high precision) increase as time structuredness decreases?

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1) What is time structuredness?

2) Why is time structuredness important?

Experiment 3

Question: Do the number of measurements and sample sizes needed to obtain high model performance (i.e., low bias, high precision) increase as time structuredness decreases?

1) What is time structuredness?

2) Why is time structuredness important?

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Time structuredness: the extent to which the same response schedule characterizes how participants provide data over time

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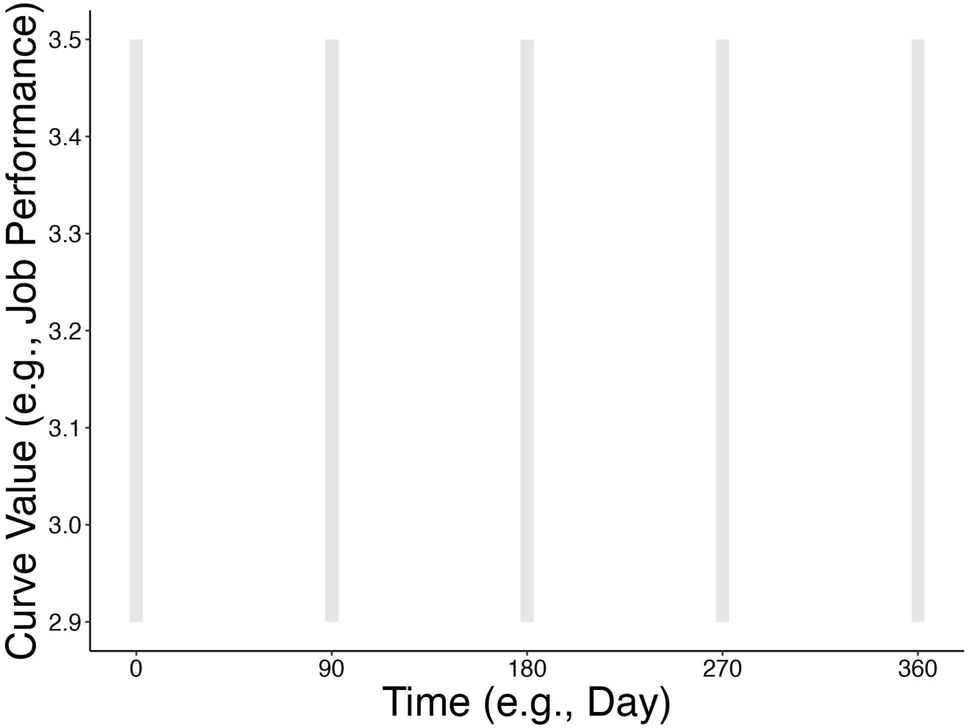
Mehta & West (2000); Mehta & Neale (2005)

Time structuredness: the extent to which the same response schedule characterizes how participants provide data over time

Time-structured data (same response schedule)



Mehta & West (2000); Mehta & Neale (2005)

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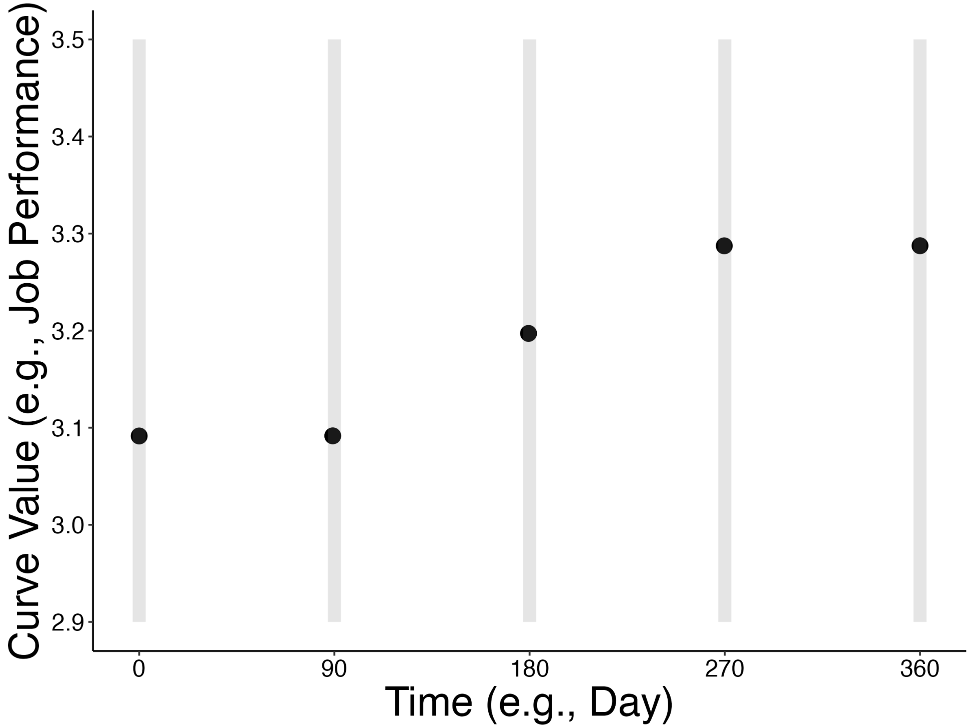
Time-structured data (same response schedule)



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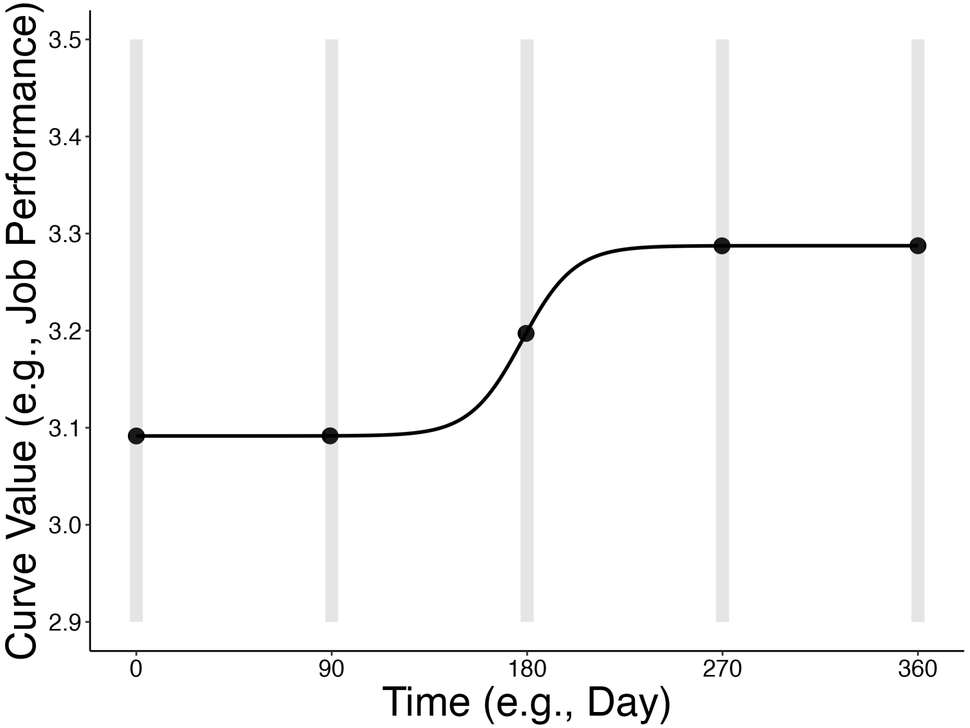
Time-structured data (same response schedule)



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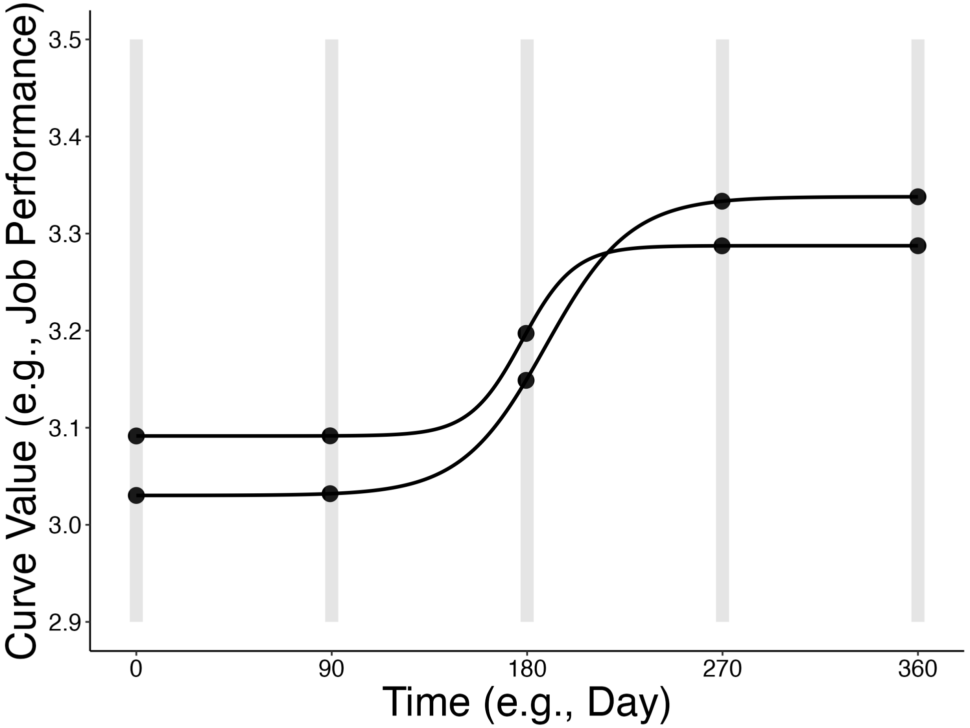
Time-structured data (same response schedule)



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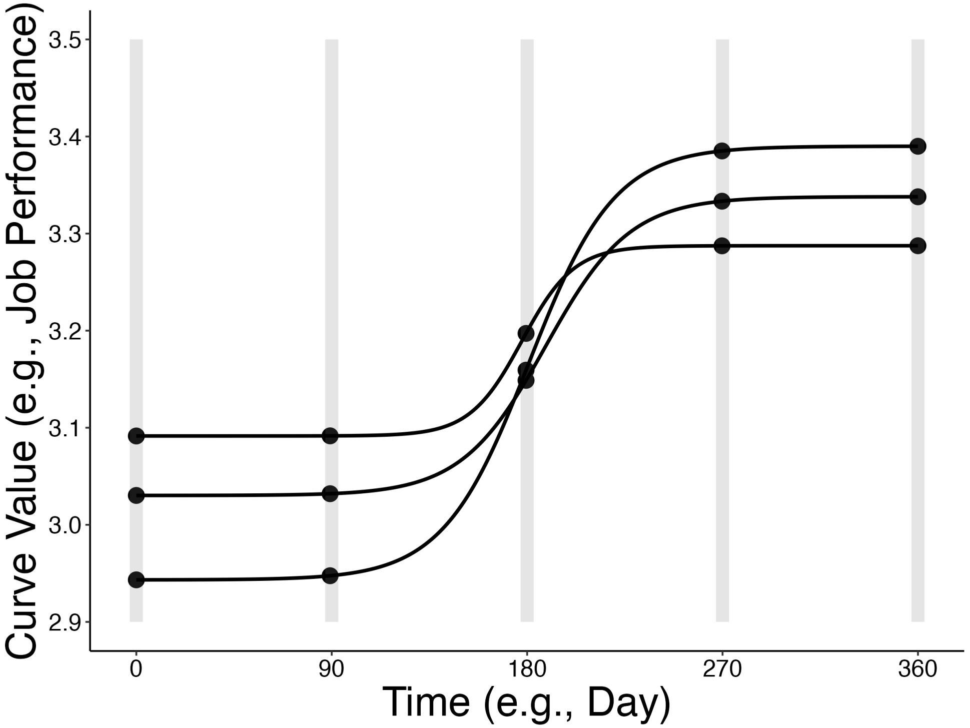
Time-structured data (same response schedule)



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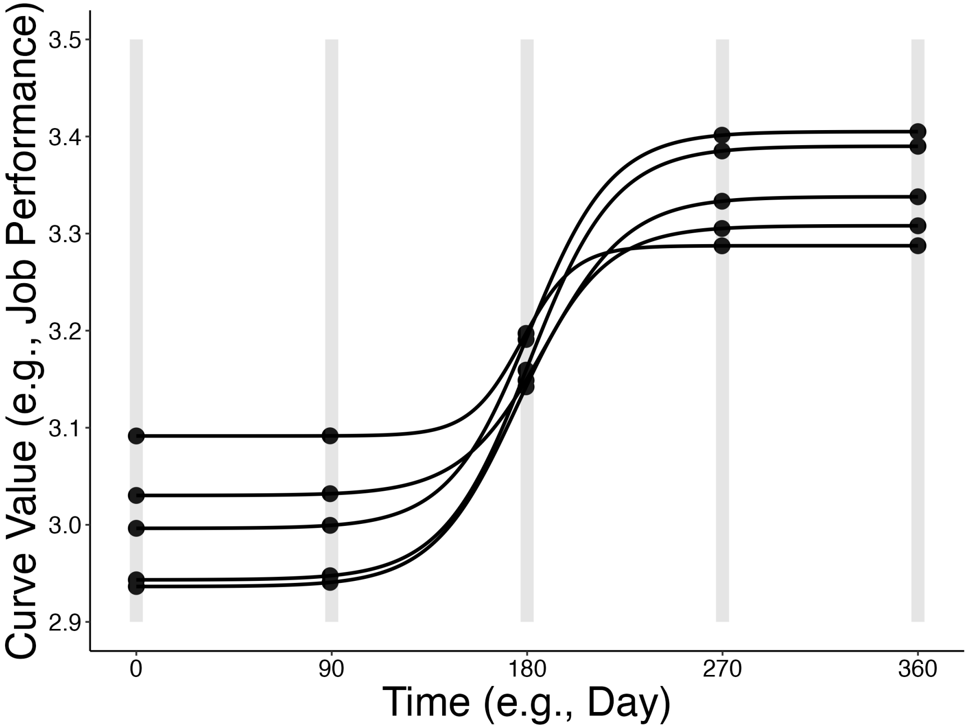
Time structuredness: the extent to which the same response schedule characterizes how participants provide data over time

Time-structured data (same response schedule)



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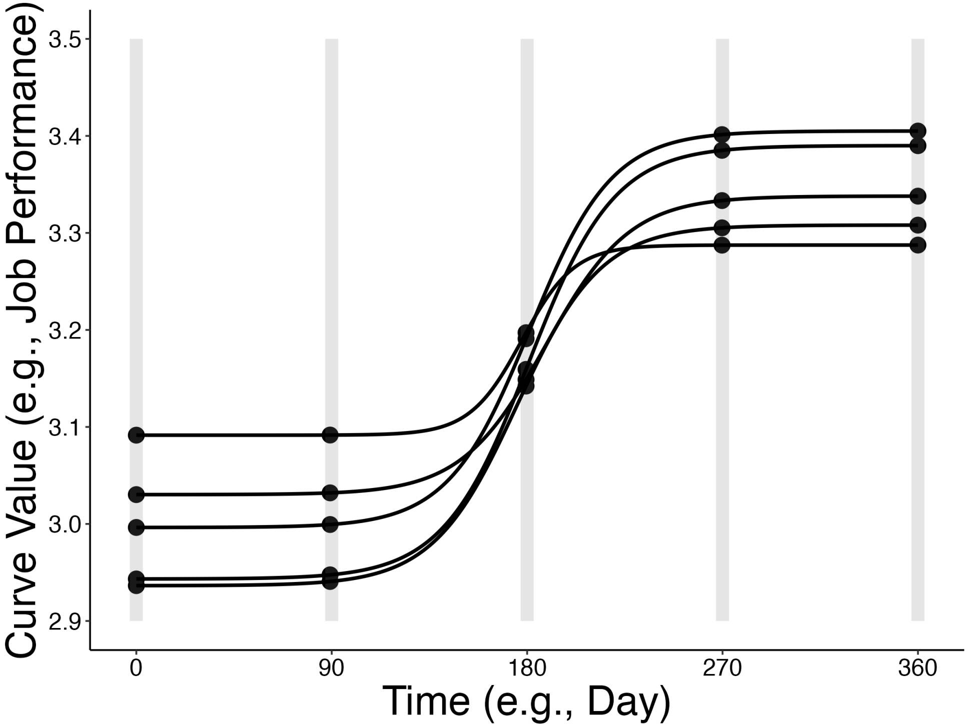
Mehta & West (2000); Mehta & Neale (2005)

Time structuredness: the extent to which the same response schedule characterizes how participants provide data over time

Time-structured data (same response schedule)

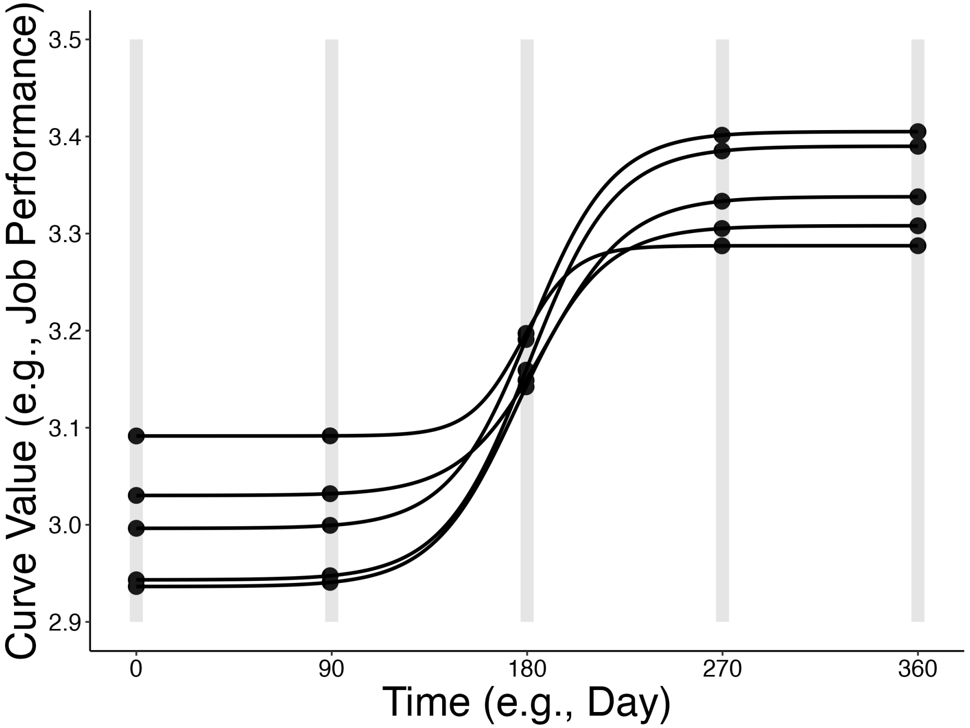


Time-unstructured data

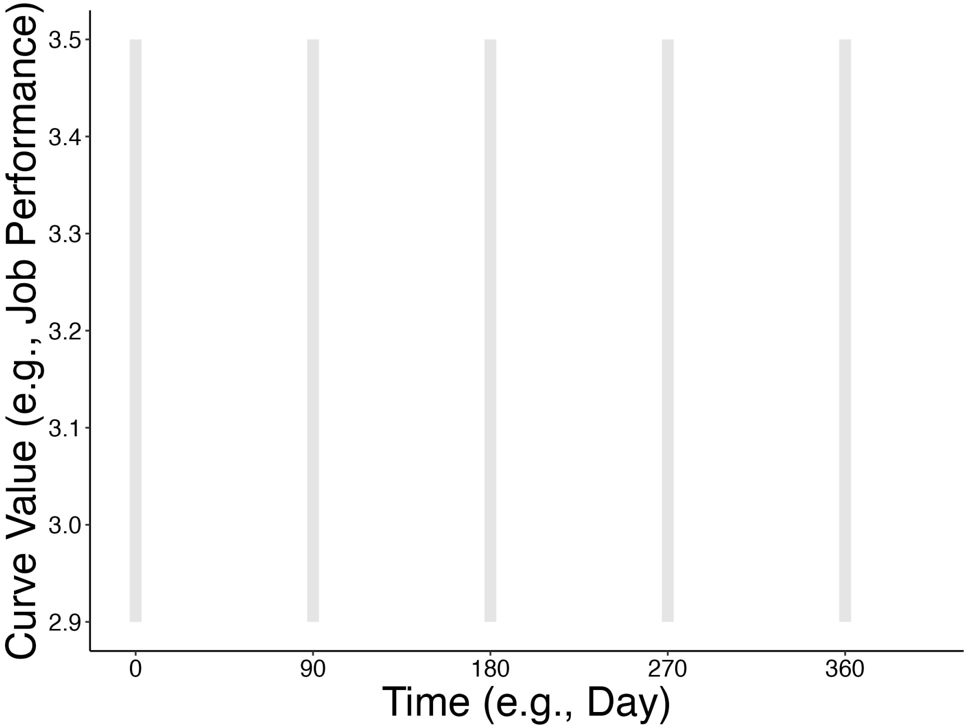
Mehta & West (2000); Mehta & Neale (2005)

Time structuredness: the extent to which the same response schedule characterizes how participants provide data over time

Time-structured data (same response schedule)



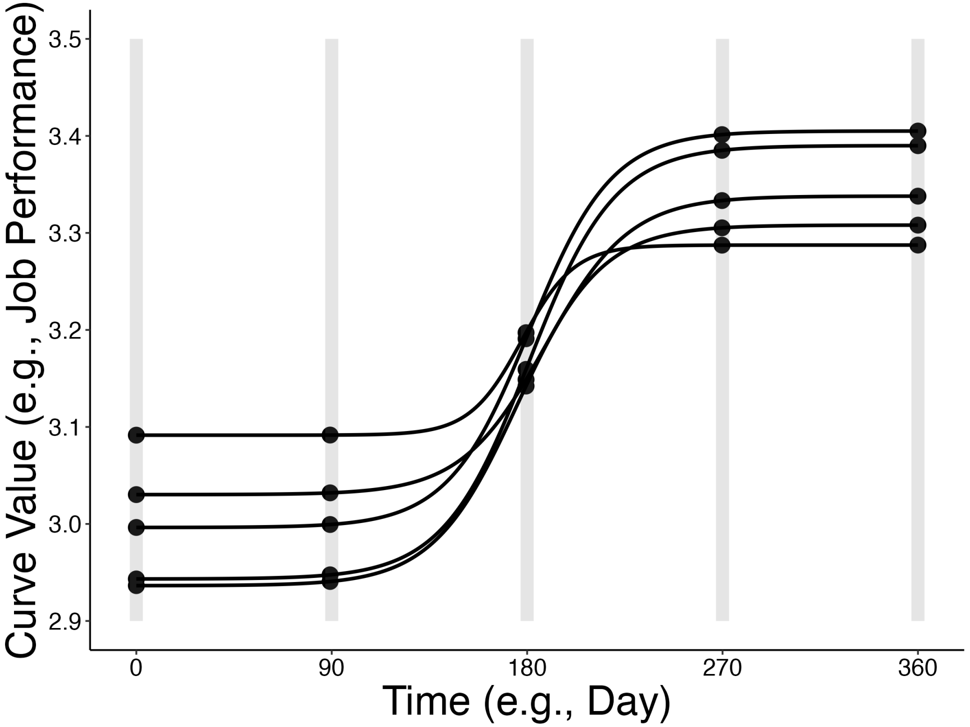
Time-unstructured data (different response schedules)



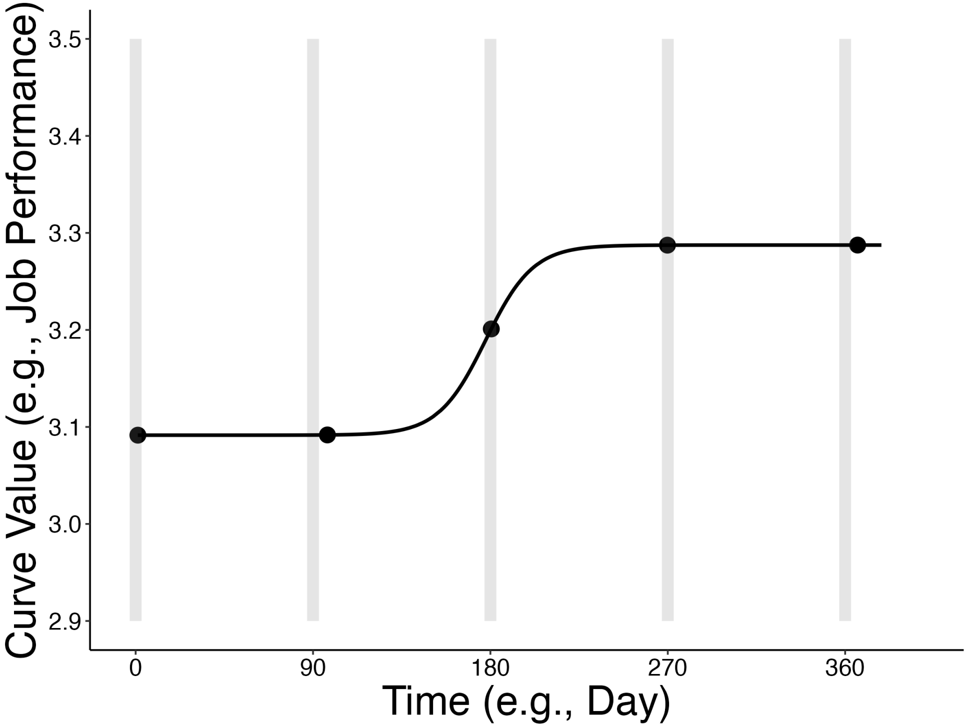
Mehta & West (2000); Mehta & Neale (2005)

Time structuredness: the extent to which the same response schedule characterizes how participants provide data over time

Time-structured data (same response schedule)



Time-unstructured data (different response schedules)



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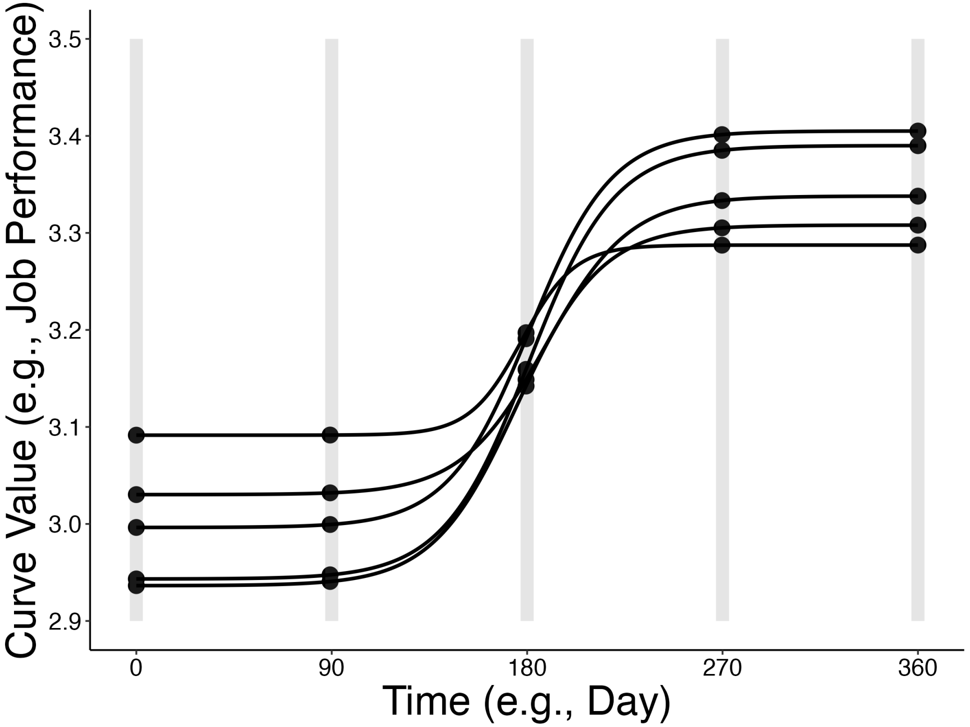
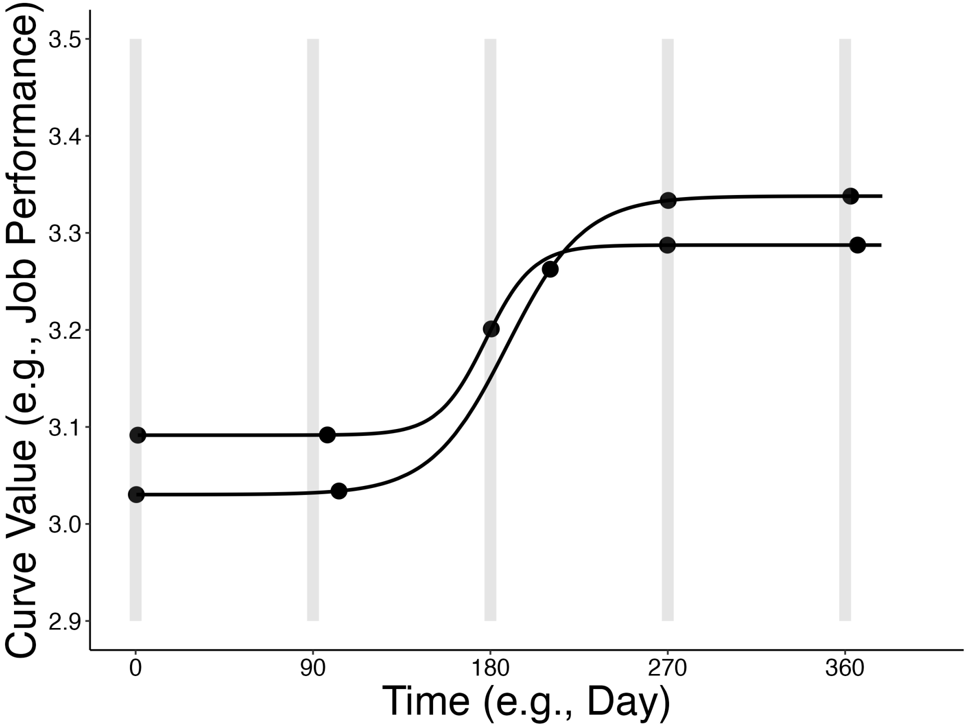
Time structuredness: the extent to which the same response schedule characterizes how participants provide data over time

Time-structured data (same response schedule)



Time-unstructured data (different response schedules)



Mehta & West (2000); Mehta & Neale (2005)

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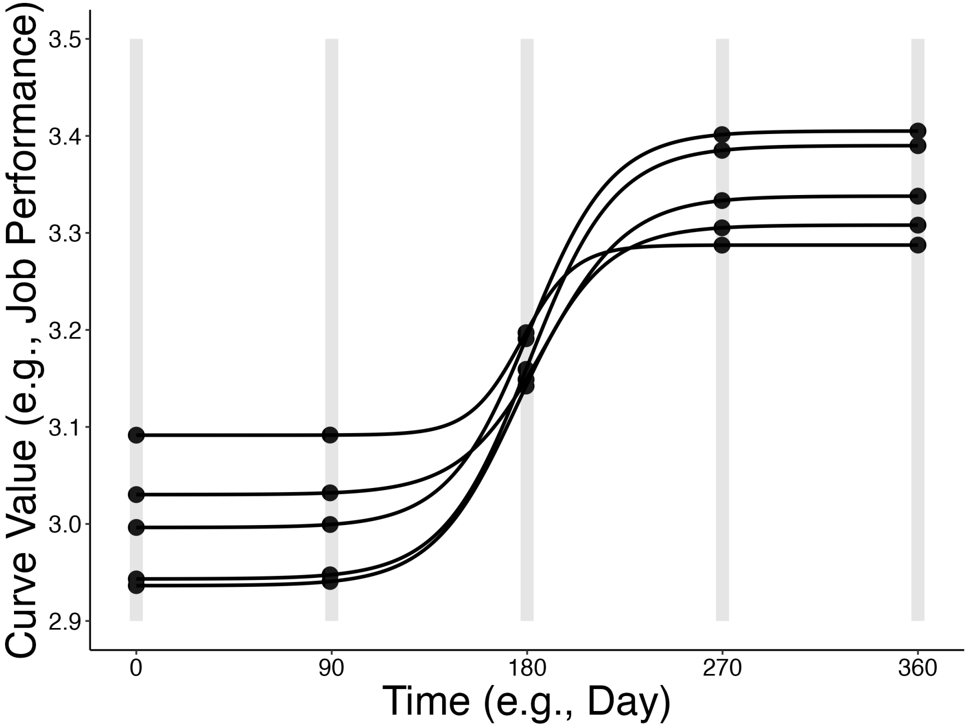
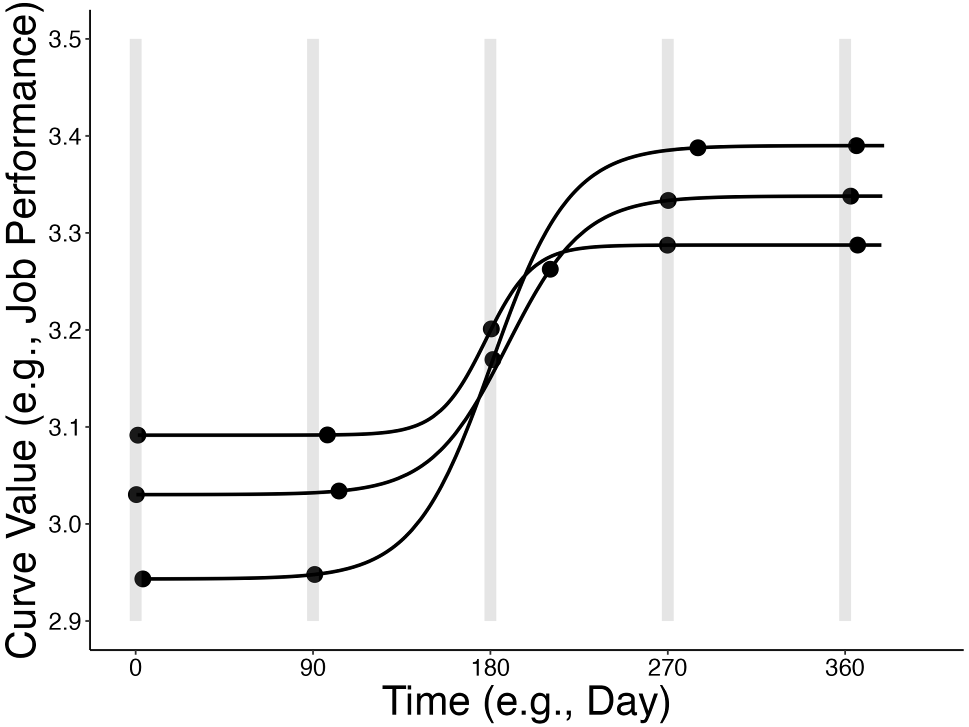
Time structuredness: the extent to which the same response schedule characterizes how participants provide data over time

Time-structured data (same response schedule)



Time-unstructured data (different response schedules)



Mehta & West (2000); Mehta & Neale (2005)

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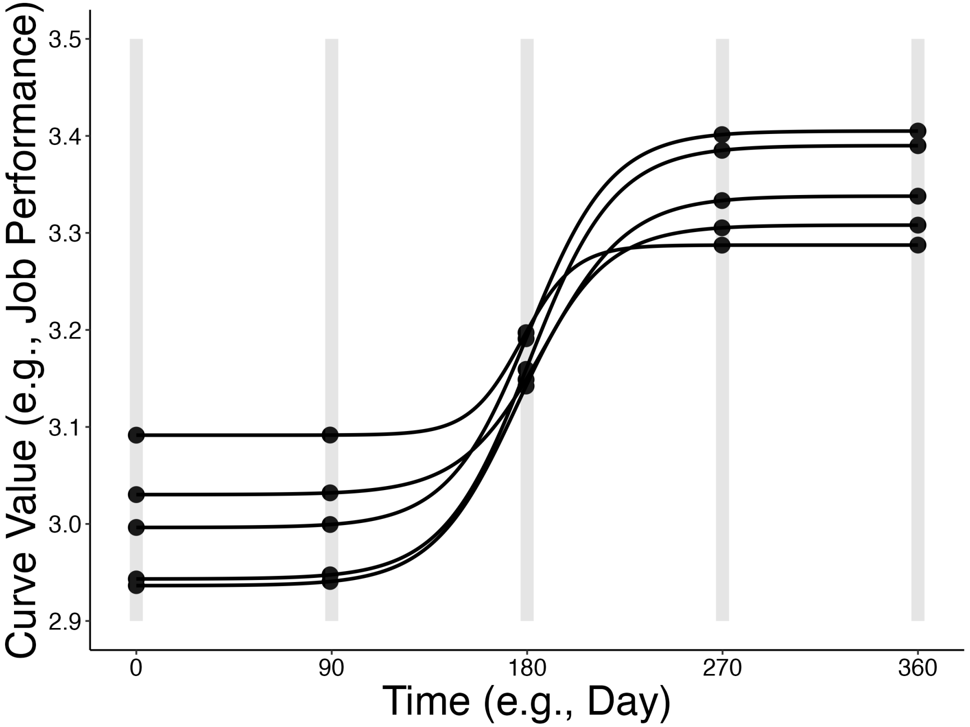
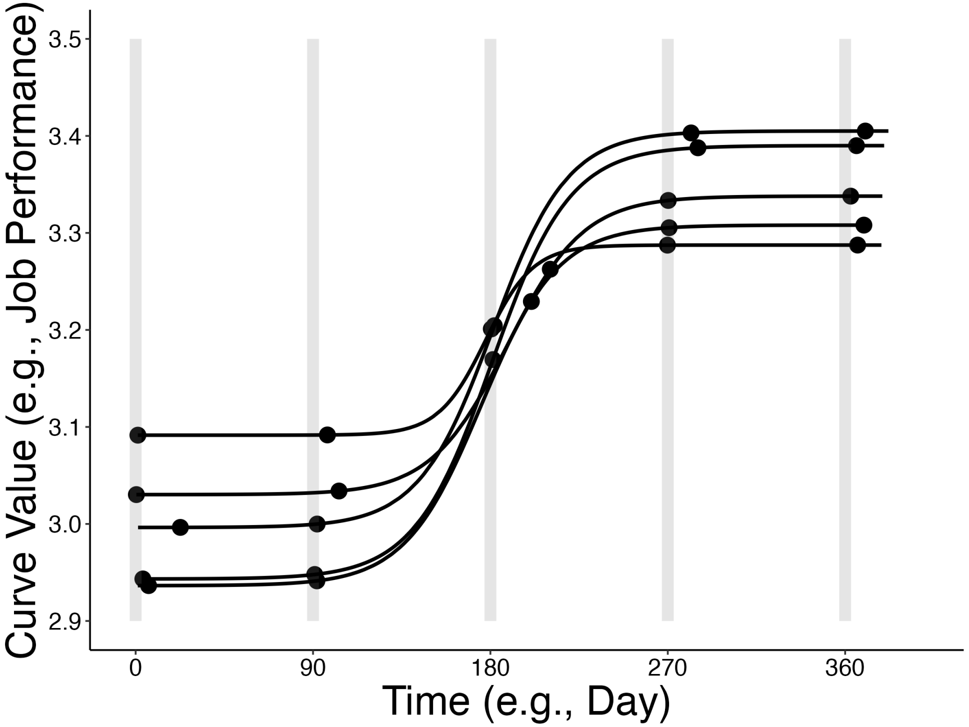
Time structuredness: the extent to which the same response schedule characterizes how participants provide data over time

Time-structured data (same response schedule)



Time-unstructured data (different response schedules)



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Mehta & West (2000); Mehta & Neale (2005)

Experiment 3

Question: Do the number of measurements and sample sizes needed to obtain high model performance (i.e., low bias, high precision) increase as time structuredness decreases?

1) What is time structuredness?

The extent to which the same response schedule characterizes how participants provide data over time

2) Why is time structuredness important?

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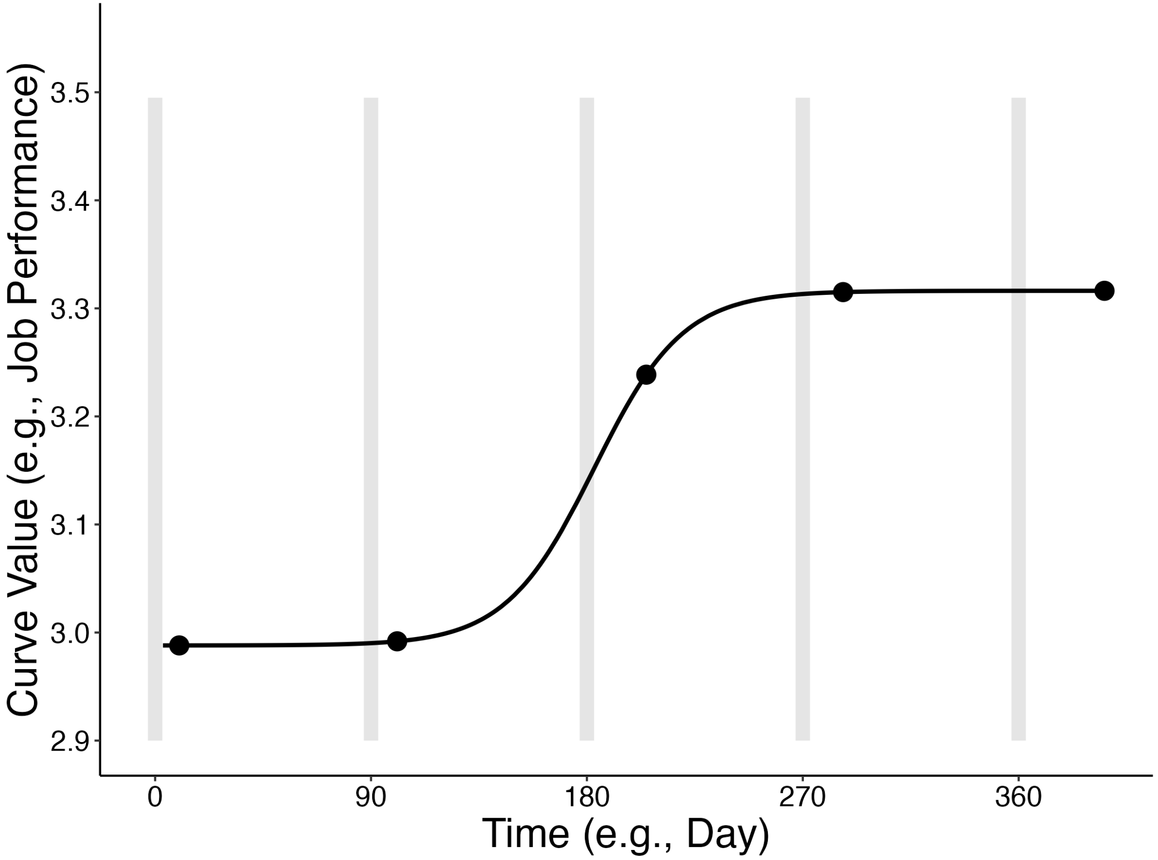

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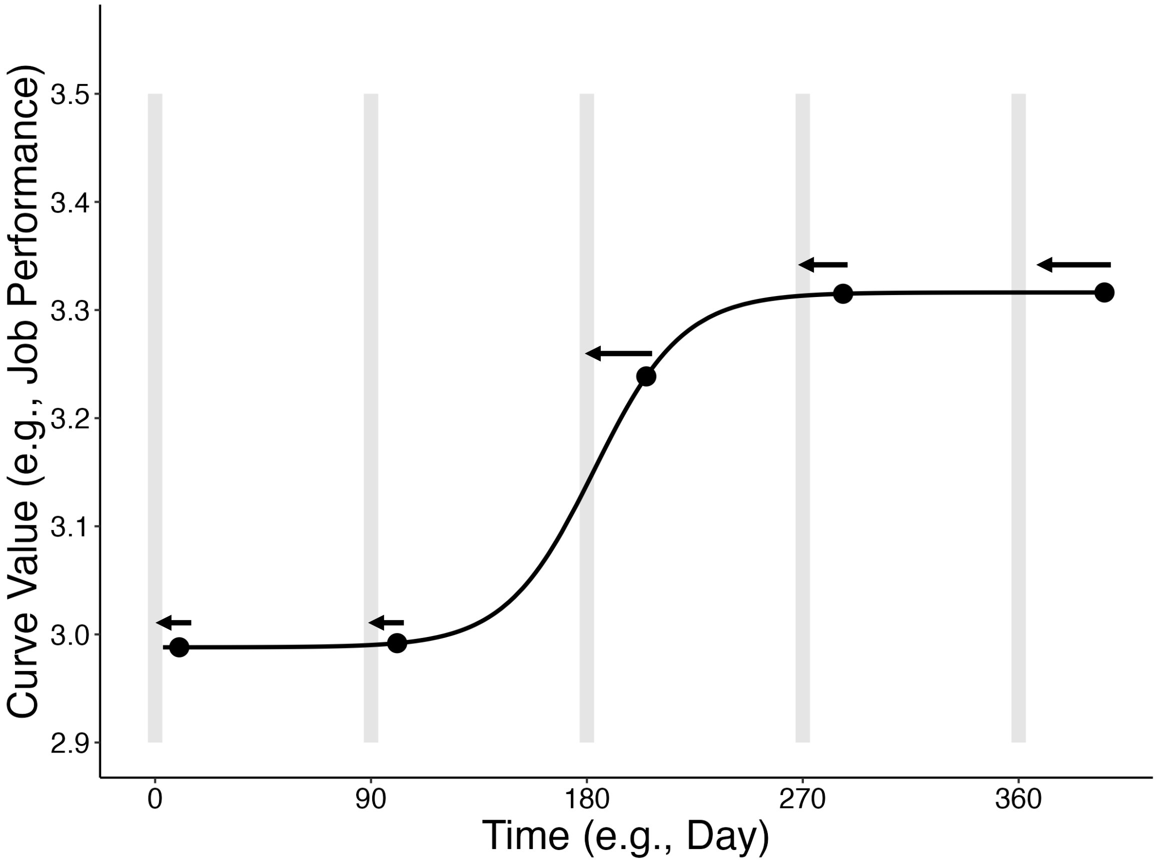

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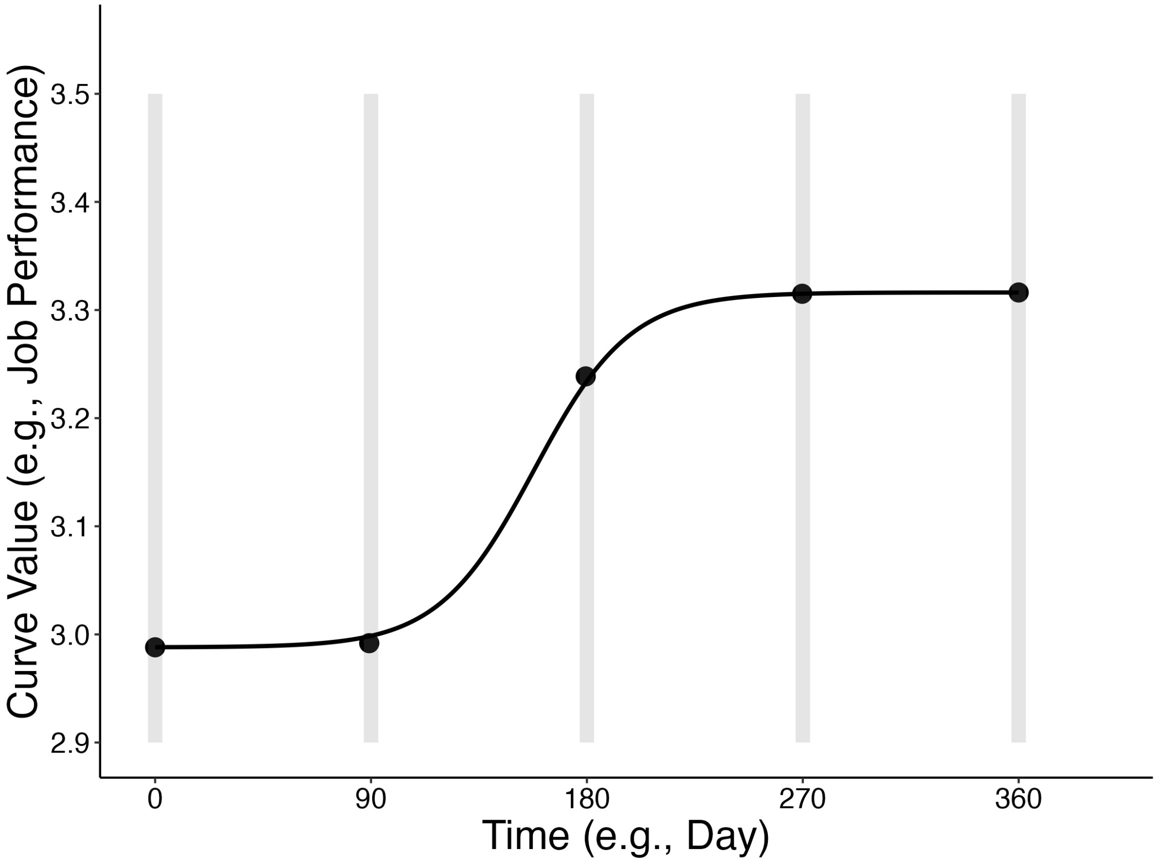
By assuming one response pattern (i.e., time-structured data), individual curves are shifted to fit this response pattern and result in considerable error



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Experiment 3

Question: Do the number of measurements and sample sizes needed to obtain high model performance (i.e., low bias, high precision) increase as time structuredness decreases?

1) What is time structuredness?

   The extent to which the same response schedule characterizes how participants provide data over time

2) Why is time structuredness important?

   Considerable error can be incurred if a model assuming time-structured data is used to analyse time-unstructured data

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Experiment 3 – Systematic Review

Number of measurements

Spacing of measurements

Sample size

Time structuredness

Few guidelines

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Effect	Nonlinear pattern
Main effects	
Number of measurements (NM)	6 studies
Spacing of measurements (SM)	1 study
Time structuredness (TS)	1 study
Sample size (S)	7 studies

Effect	Nonlinear pattern
Main effects	
Number of measurements (NM)	6 studies
Spacing of measurements (SM)	1 study
Time structuredness (TS)	1 study
Sample size (S)	7 studies
Two-way interactions	
NM x SM	1 study
NM x TS	**Cell 1 (Exp. 3)**
NM x S	5 studies
SM x TS	**Cell 3**
SM x S	**Cell 5 (Exp. 2)**
TS x S	2 studies

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Effect	Nonlinear pattern
Main effects	
Number of measurements (NM)	6 studies
Spacing of measurements (SM)	1 study
Time structuredness (TS)	1 study
Sample size (S)	7 studies
Two-way interactions	
NM x SM	1 study
NM x TS	**Cell 1 (Exp. 3)**
NM x S	5 studies
SM x TS	**Cell 3**
SM x S	**Cell 5 (Exp. 2)**
TS x S	2 studies
Three-way interactions	
NM x SM x TS	**Cell 7**
NM x SM x S	**Cell 9 (Exp. 2)**
NM x TS x S	**Cell 10 (Exp. 3)**
SM x TS x S	**Cell 12**

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Effect	Nonlinear pattern
Main effects	
Number of measurements (NM)	6 studies
Spacing of measurements (SM)	1 study
Time structuredness (TS)	1 study
Sample size (S)	7 studies
Two-way interactions	
NM x SM	1 study
NM x TS	**Cell 1 (Exp. 3)**
NM x S	5 studies
SM x TS	**Cell 3**
SM x S	**Cell 5 (Exp. 2)**
TS x S	2 studies
Three-way interactions	
NM x SM x TS	**Cell 7**
NM x SM x S	**Cell 9 (Exp. 2)**
NM x TS x S	**Cell 10 (Exp. 3)**
SM x TS x S	**Cell 12**

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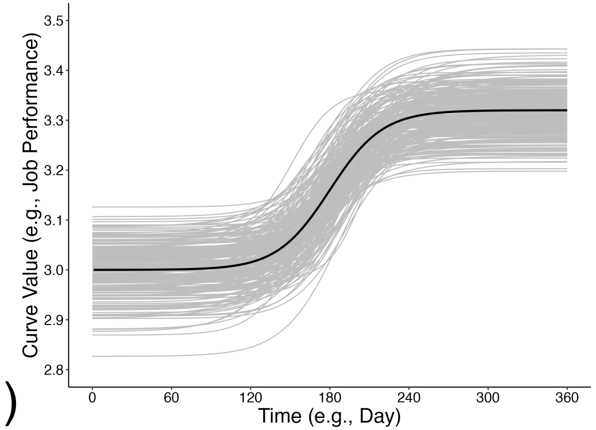
Experiment 3 design (Monte Carlo method)

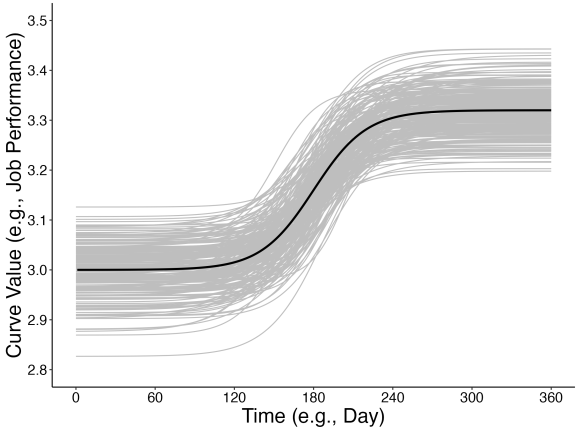
◯ (dashed) = model
◯ = sample

1. Population definition

$\theta, \alpha, \beta, \gamma_{\text{fixed + random}}, \varepsilon$ (known)



$\theta, \alpha, \beta, \gamma_{\text{fixed + random}}, \varepsilon$ (estimated)

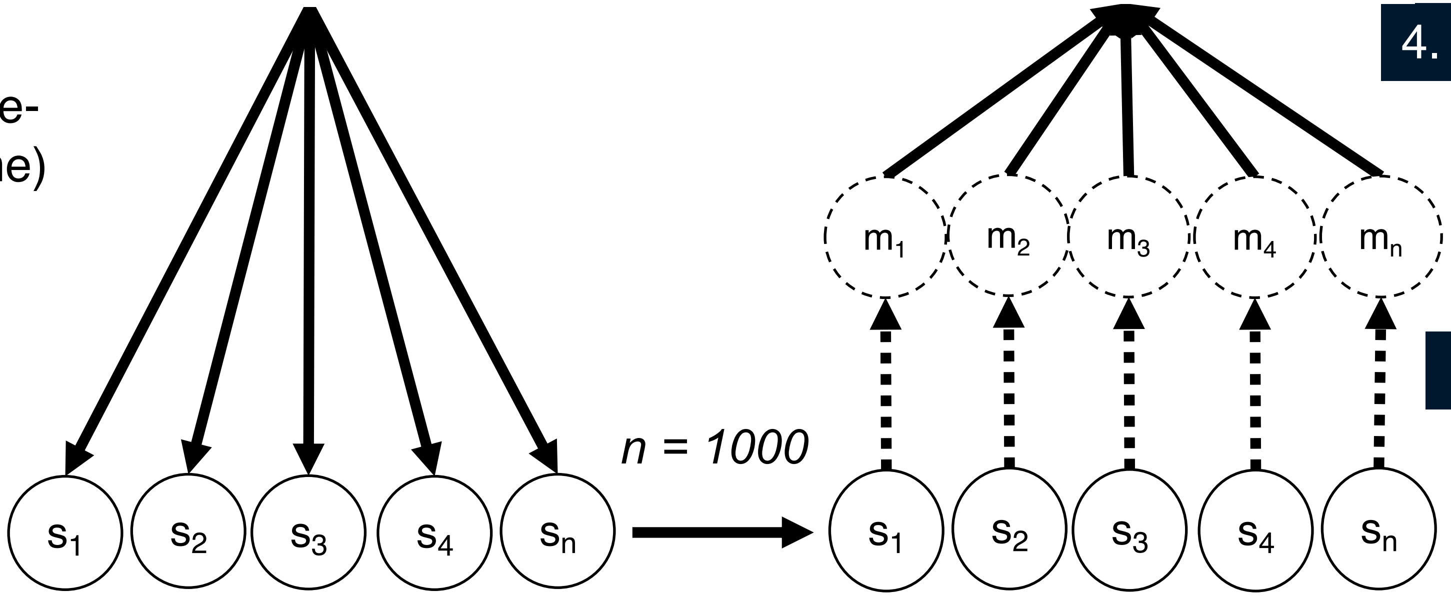


2. Sample generation

IV 1: Number of measurements (5, 7, 9, 11)

IV 2: Spacing of measurements (equal, time-inc., time dec., mid-extreme)

IV 3: Time structuredness



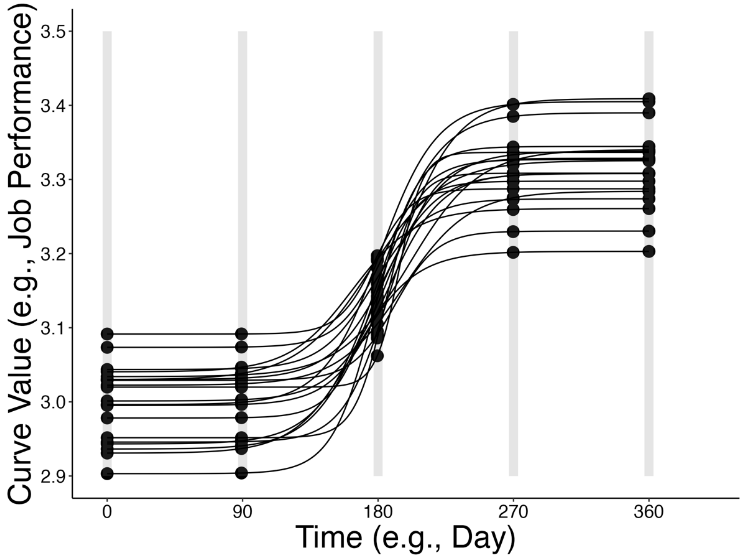
4. Model performance

Bias + precision

3. Modelling

Structured latent growth model

Time-structured data
(High time structuredness)

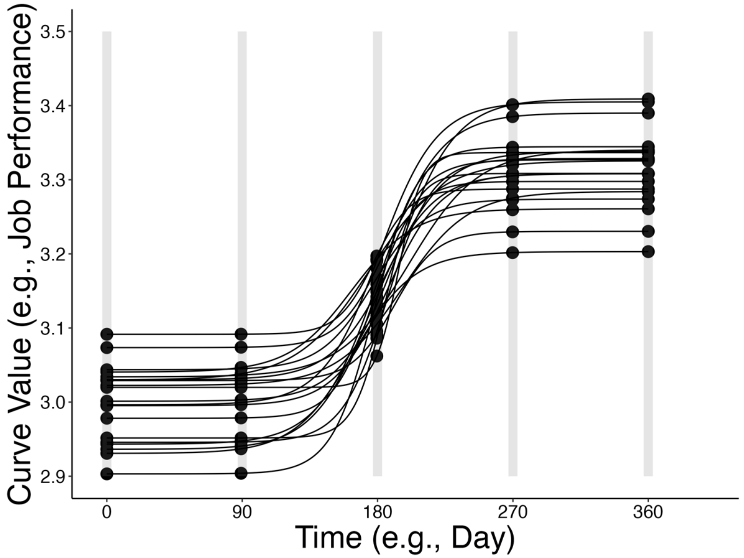


Momentary response window
(immediate response rate)

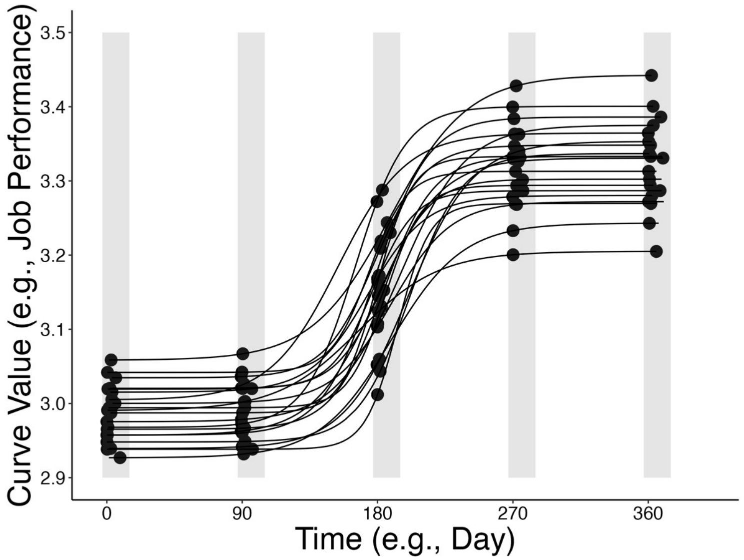
High	*Time structuredness*	*Low*
Short	*Response window length*	*Long*
Fast	*Response rate*	*Slow*

Coulombe (2016)

Time-structured data (High time structuredness)



Medium time structuredness



Momentary response window (immediate response rate)

Short response window (fast response rate)

High	Time structuredness	Low
Short	Response window length	Long
Fast	Response rate	Slow

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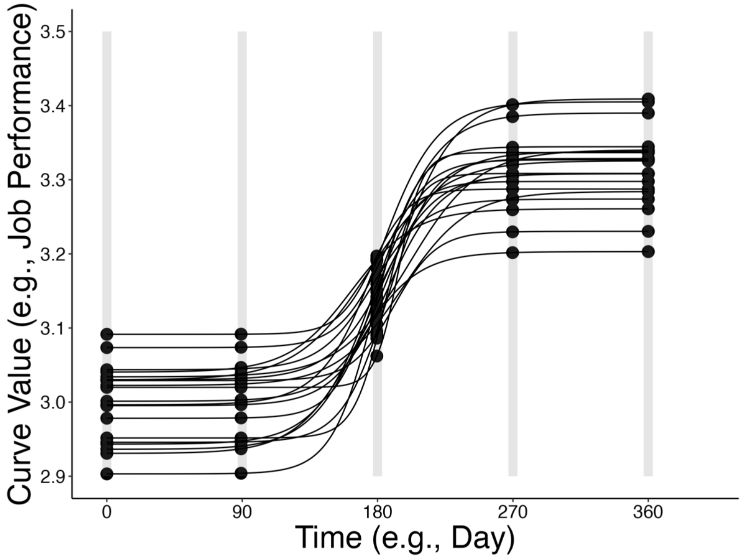
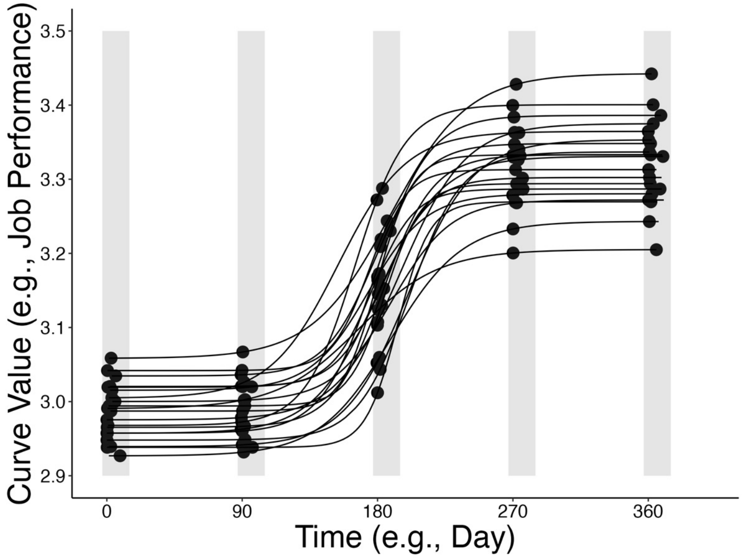
Coulombe (2016)

Time-structured data (High time structuredness)



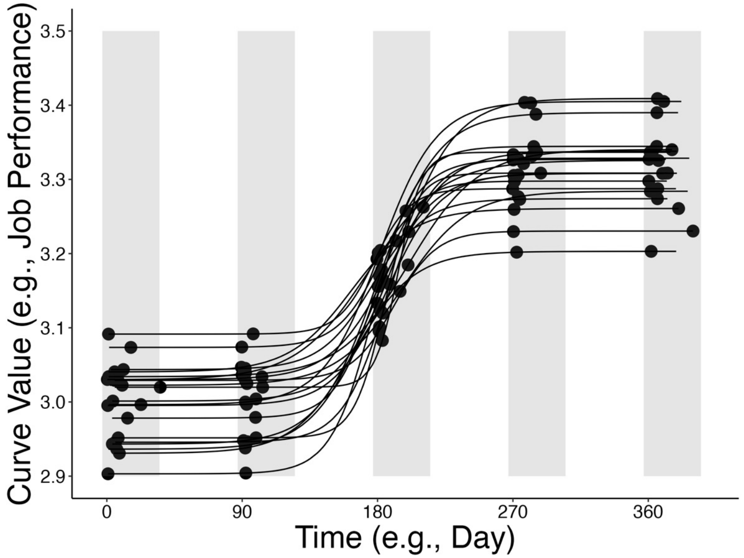
Momentary response window (immediate response rate)

Medium time structuredness



Short response window (fast response rate)

Low time structuredness

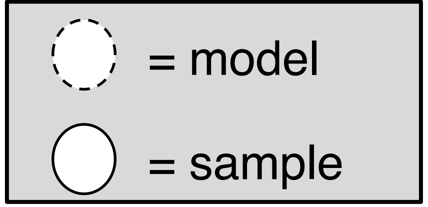


Long response window (slow response rate)

High	*Time structuredness*	Low
Short	*Response window length*	Long
Fast	*Response rate*	Slow

Coulombe (2016)

Experiment 3 design (Monte Carlo method)



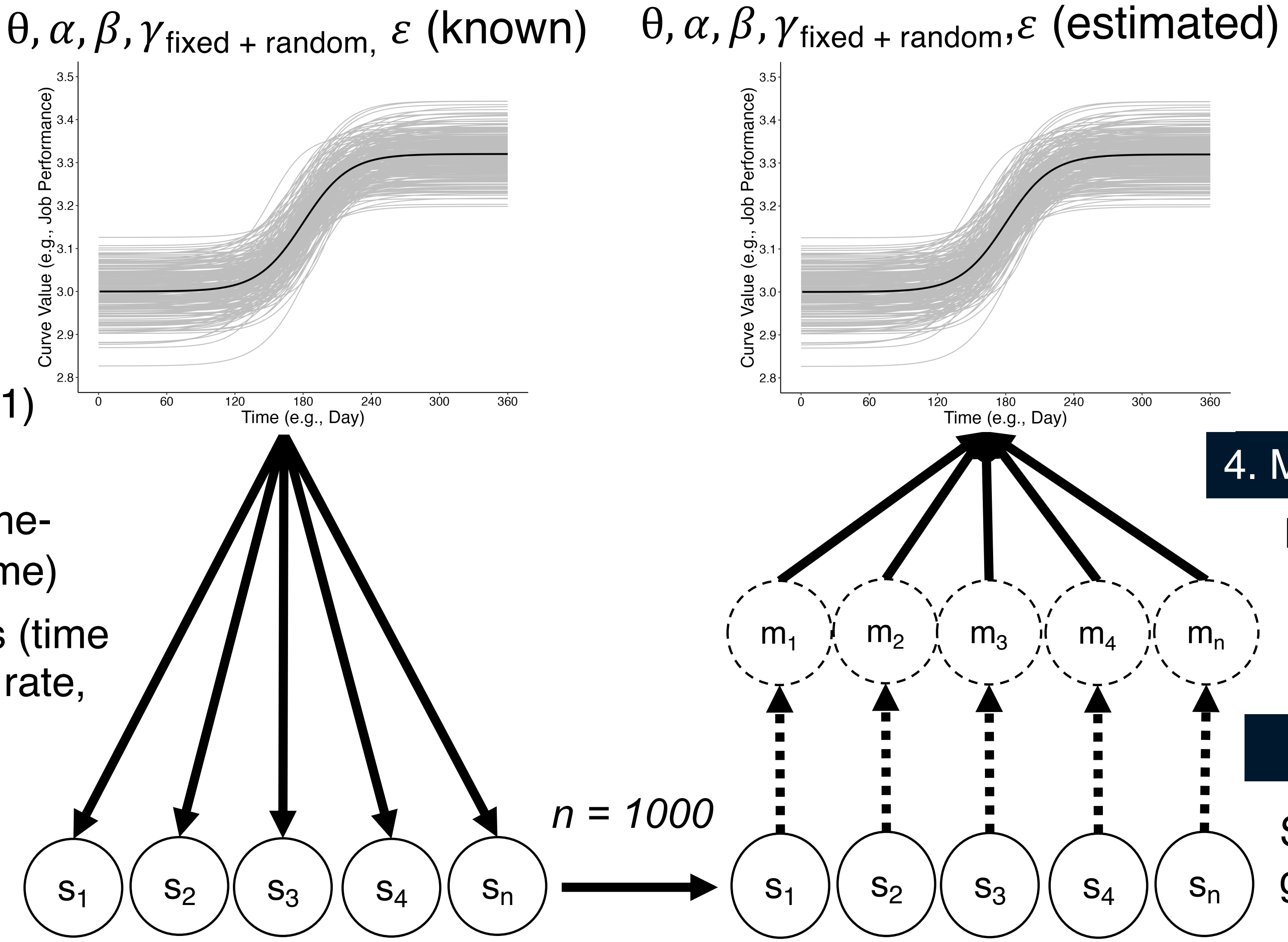
1. Population definition

2. Sample generation

IV 1: Number of measurements (5, 7, 9, 11)

IV 2: Spacing of measurements (equal, time-inc., time dec., mid-extreme)

IV 3: Time structuredness (time structured, fast response rate, slow response rate



4. Model performance

Bias + precision

3. Modelling

Structured latent growth model

Experiment 3

Question: Do the number of measurements and sample sizes needed to obtain high model performance (i.e., low bias, high precision) increase as time structuredness decreases?

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Experiment 3

Question: Do the number of measurements and sample sizes needed to obtain high model performance (i.e., low bias, high precision) increase as time structuredness decreases?

Answer: Bias systematically increases as time structuredness decreases

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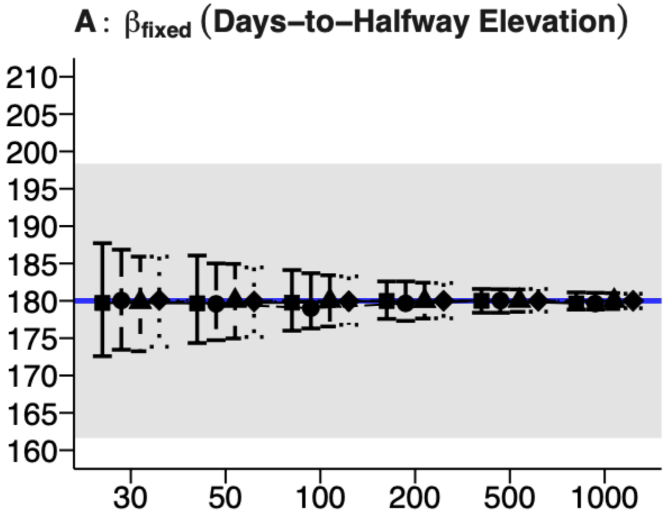
Answer: Bias systematically increases as time structuredness decreases

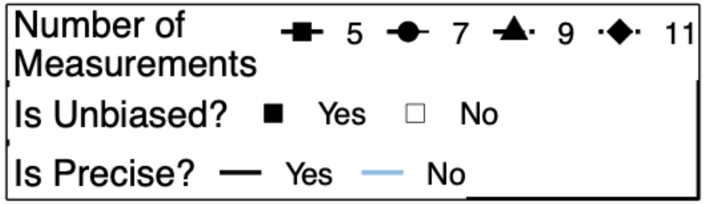
High *Time structuredness* *Low*

Fast *Response rate* *Slow*

Time structured data
(immediate response rate)



Sample Size (*N*)

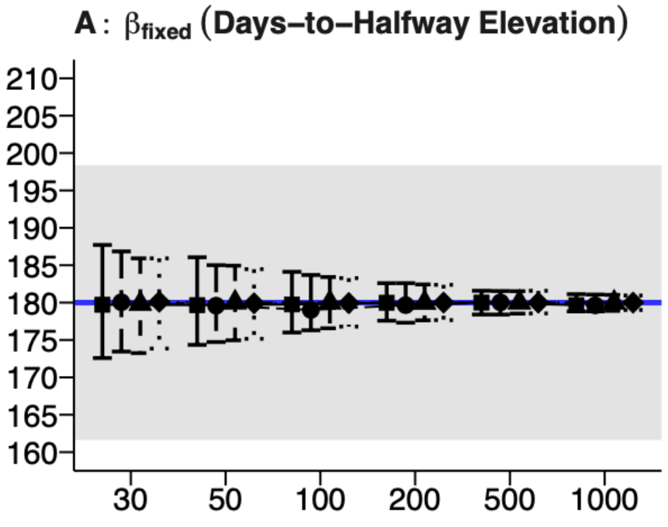


Answer: Bias systematically increases as time structuredness decreases

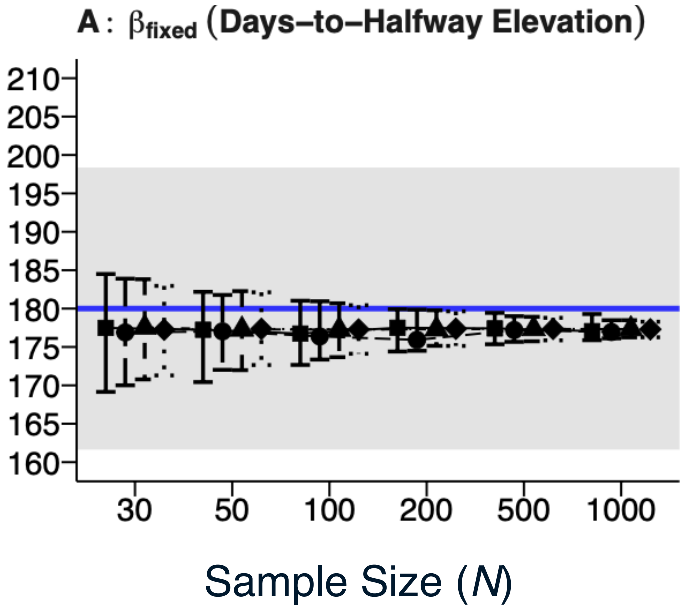
High — *Time structuredness* — *Low*

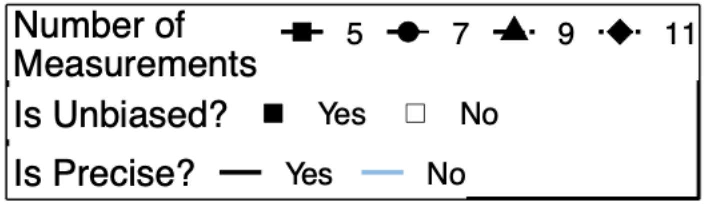
Fast — *Response rate* — *Slow*

Time structured data (immediate response rate)



Fast response rate





Answer: Bias systematically increases as time structuredness decreases

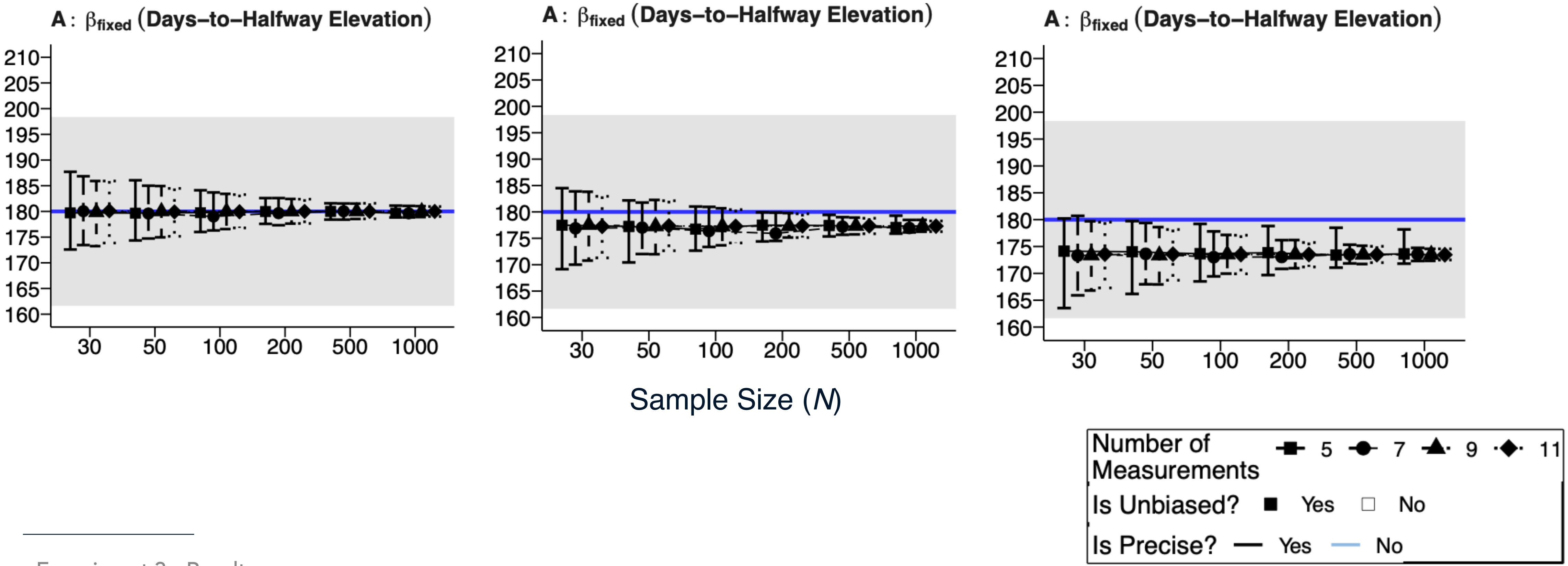
High — *Time structuredness* — *Low*

Fast — *Response rate* — *Slow*

Time structured data (immediate response rate)

Fast response rate

Slow response rate



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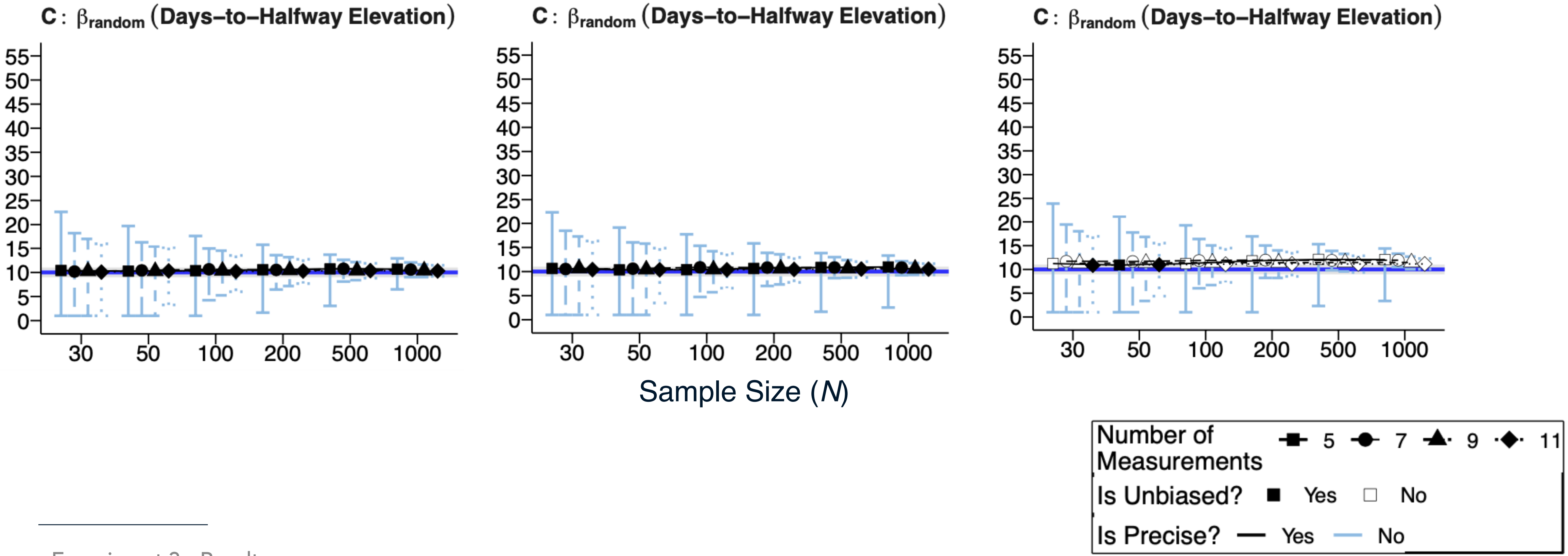
Answer: Bias systematically increases as time structuredness decreases

High *Time structuredness* *Low*

Fast *Response rate* *Slow*

Time structured data (immediate response rate) *Fast response rate* *Slow response rate*



Answer: Bias systematically increases as time structuredness decreases

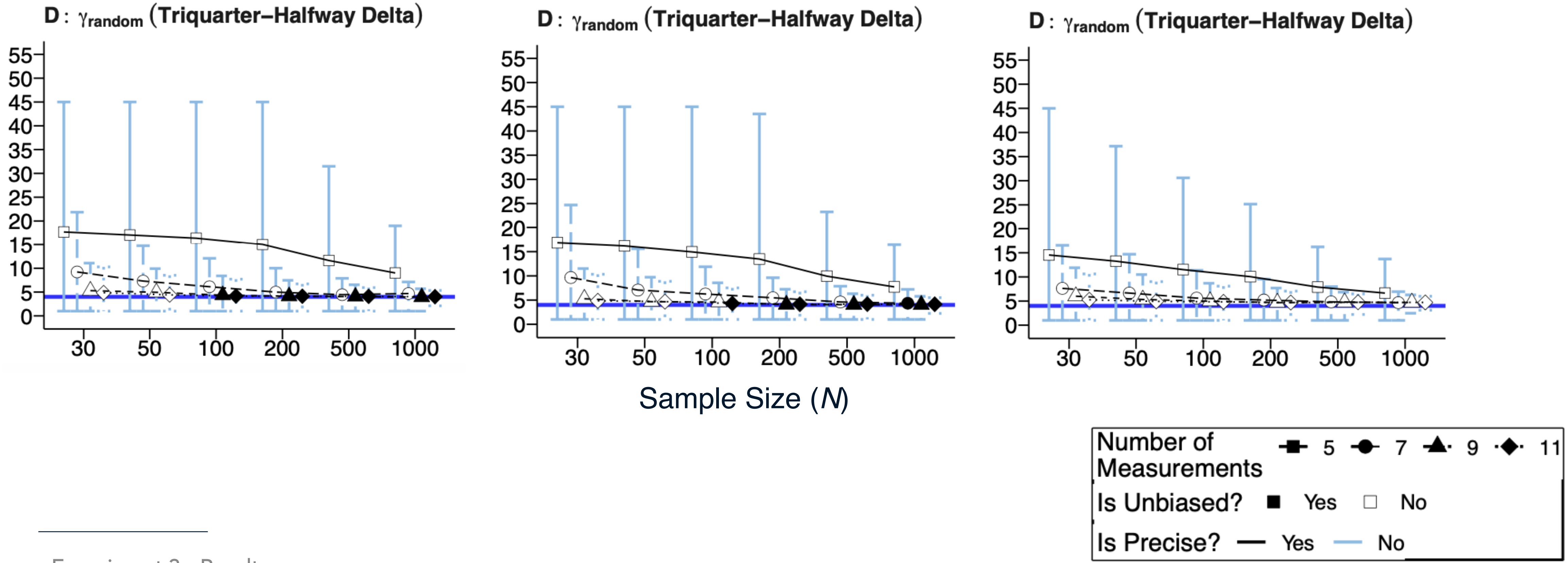
High *Time structuredness* *Low*

Fast *Response rate* *Slow*

Time structured data (immediate response rate)

Fast response rate

Slow response rate



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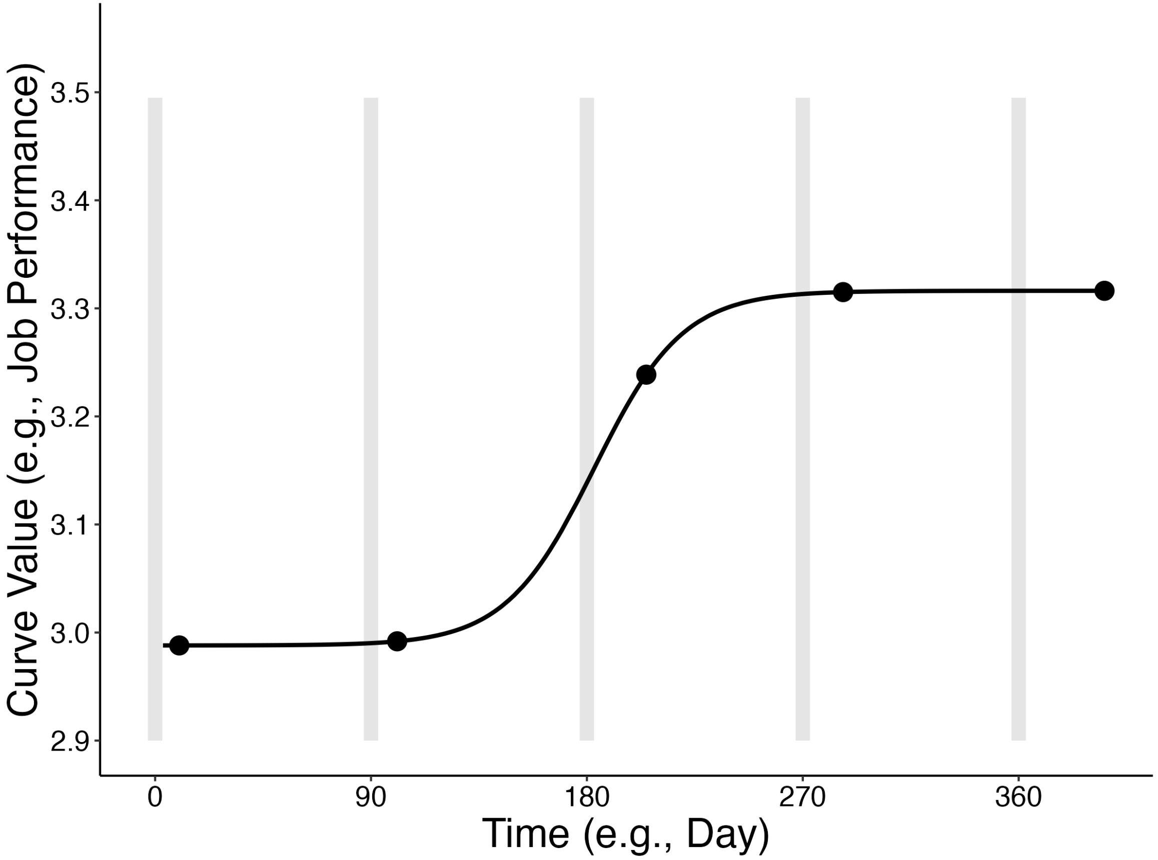
By assuming one response pattern, all individual curves are shifted to fit this response pattern



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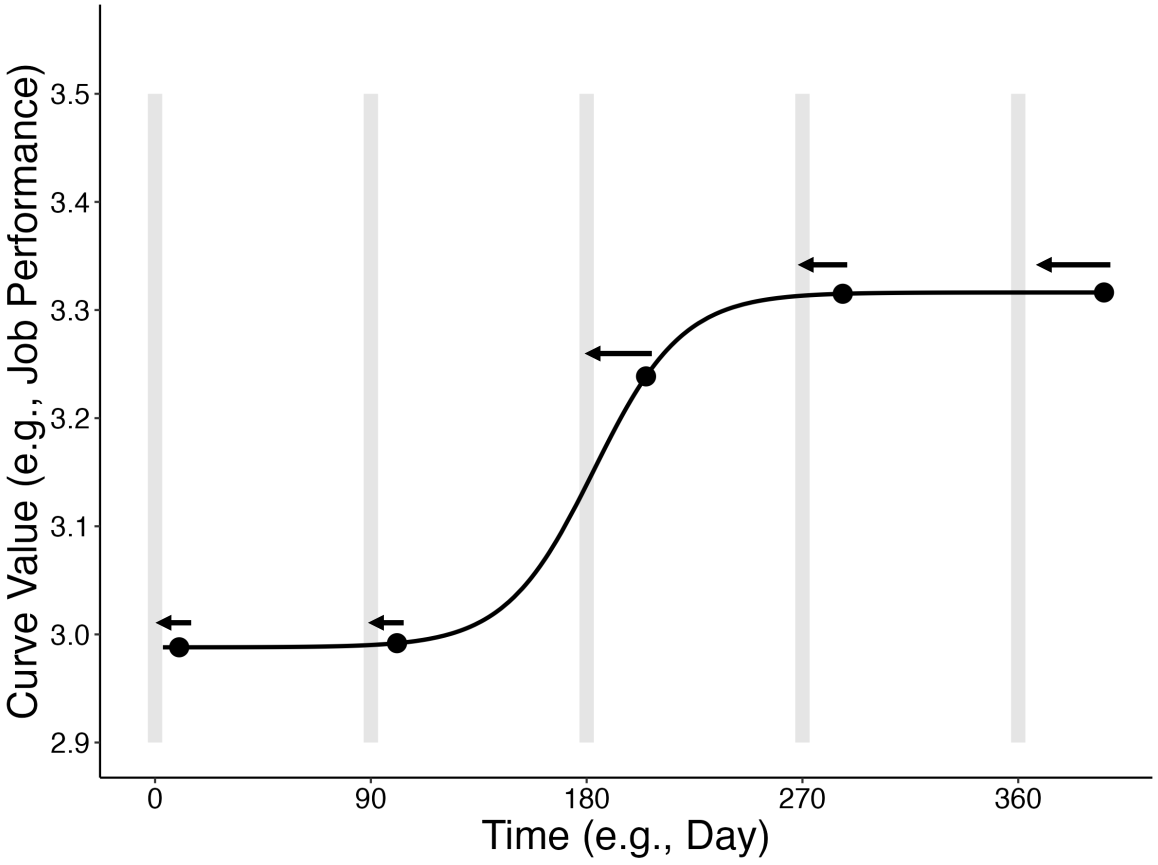

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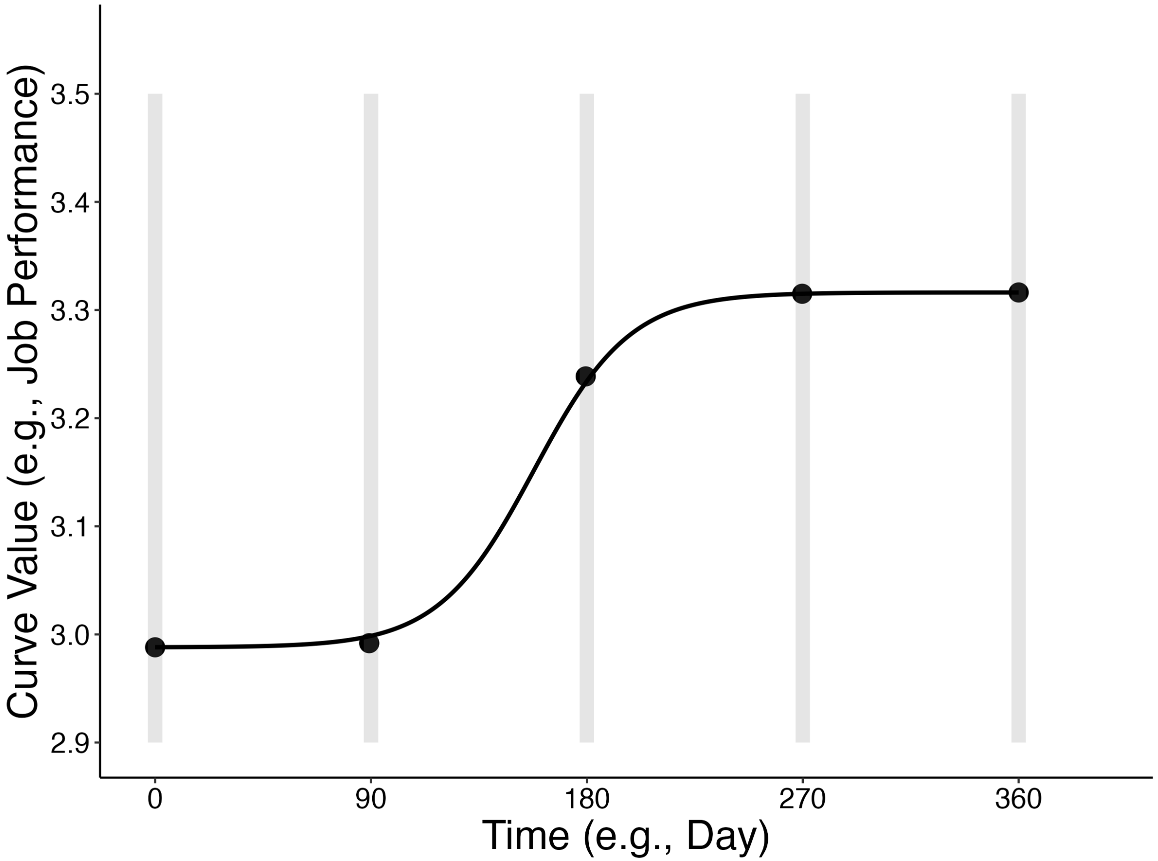

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Experiment 3 design (Monte Carlo method)

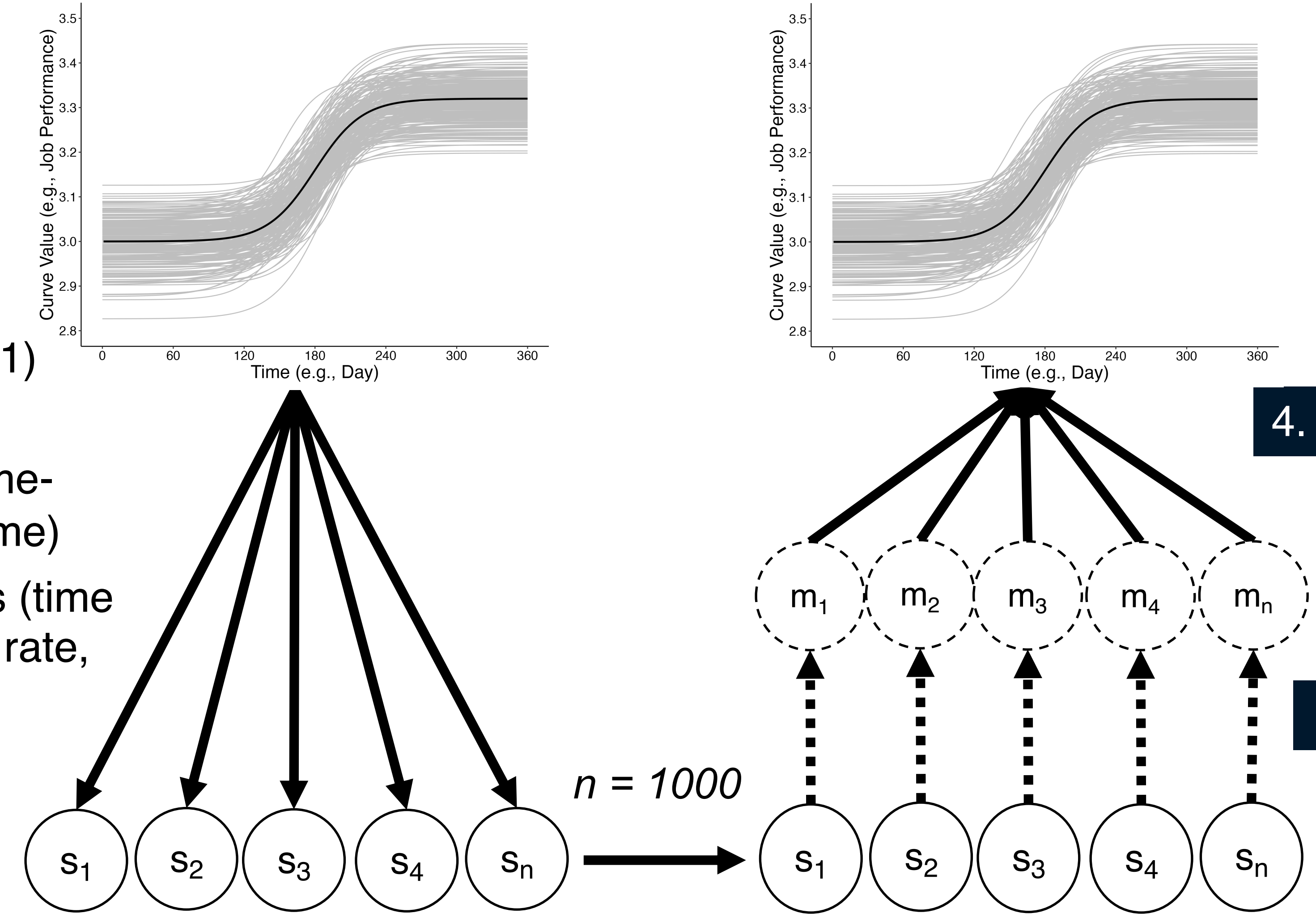
= model

= sample

1. Population definition

$\theta, \alpha, \beta, \gamma_{\text{fixed + random}}, \varepsilon$ (known)

$\theta, \alpha, \beta, \gamma_{\text{fixed + random}}, \varepsilon$ (estimated)



2. Sample generation

IV 1: Number of measurements (5, 7, 9, 11)

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IV 3: Time structuredness (time structured, fast response rate, slow response rate

4. Model performance

Bias + precision

3. Modelling

Structured latent growth model

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Experiment 3 design (Monte Carlo method)

= model

= sample

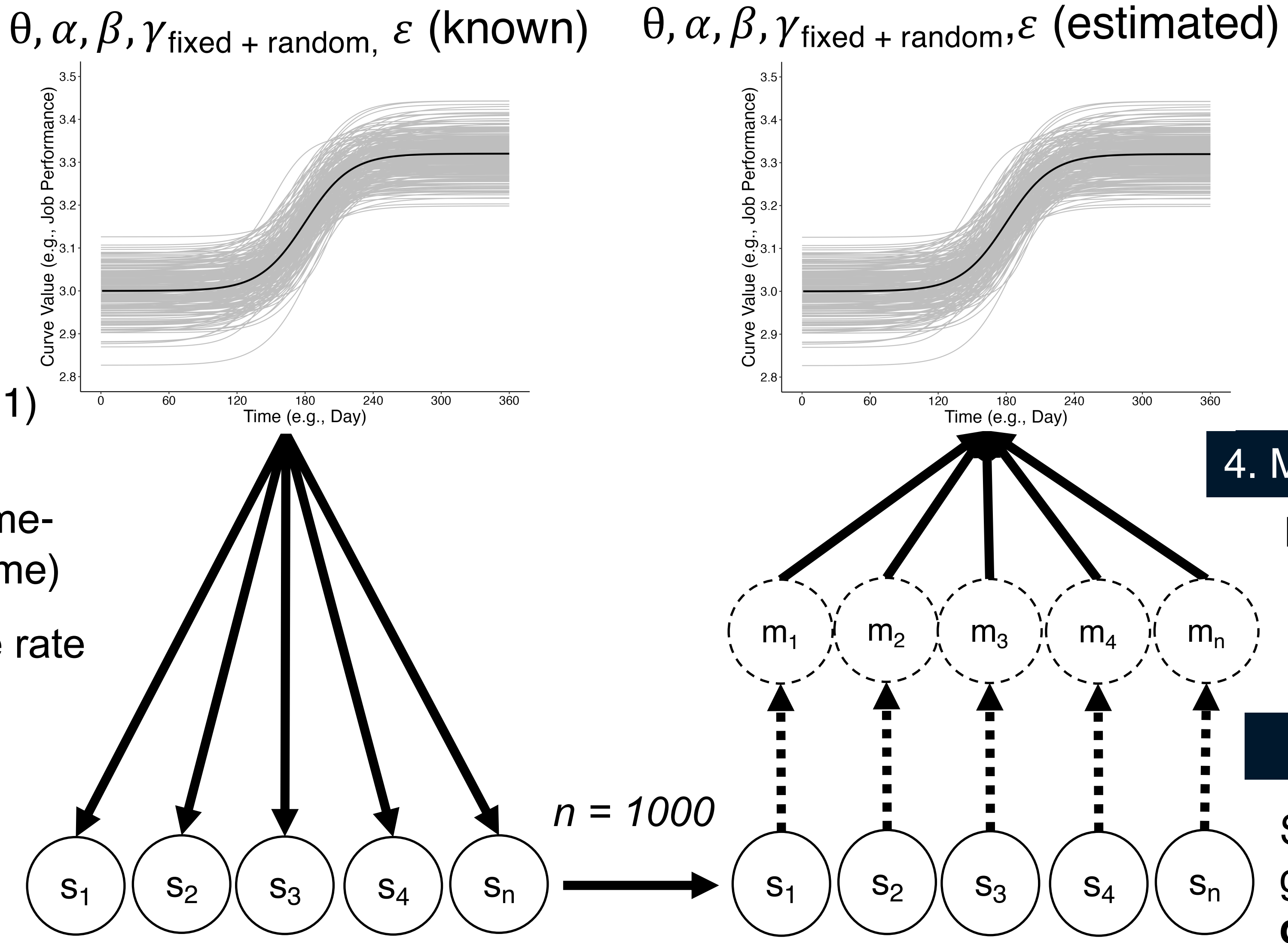
1. Population definition

2. Sample generation

IV 1: Number of measurements (5, 7, 9, 11)

IV 2: Spacing of measurements (equal, time-inc., time dec., mid-extreme)

Constant: slow response rate



4. Model performance

Bias + precision

3. Modelling

Structured latent growth model + **definition variables**

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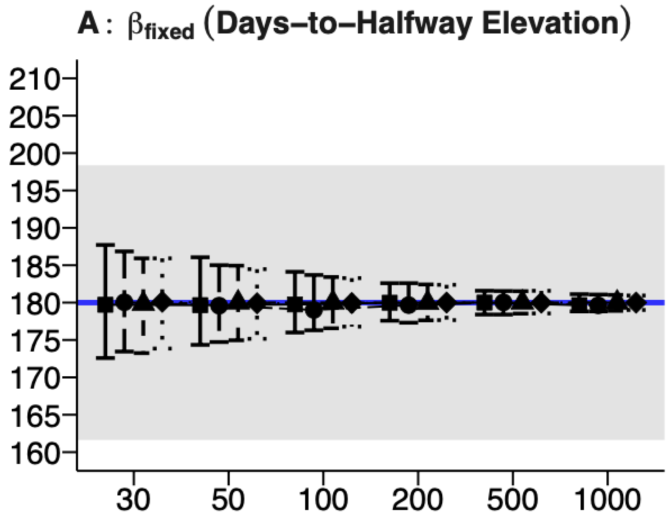
Definition variables can be used to prevent low time structurednesss from inflating bias

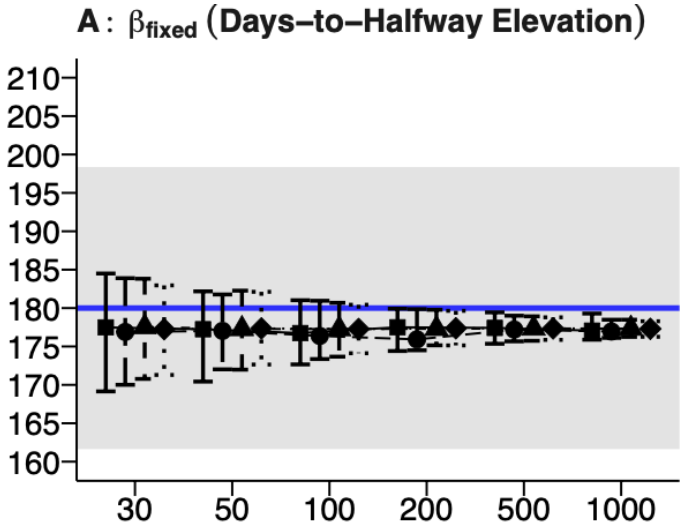
High *Time structuredness* *Low*

Fast *Response rate* *Slow*

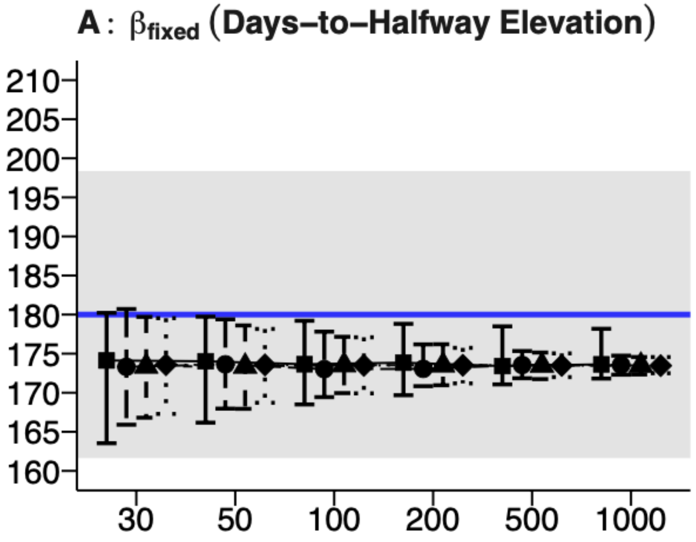
Time structured data (immediate response rate)



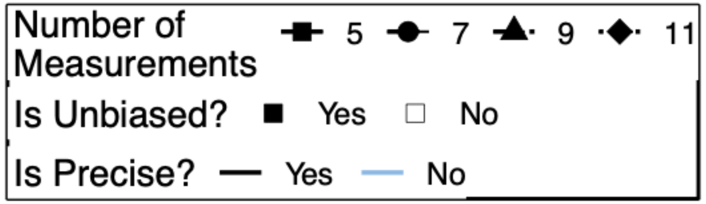
Fast response rate



Slow response rate



Sample Size (N)



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Definition variables can be used to prevent low time structurednesss from inflating bias

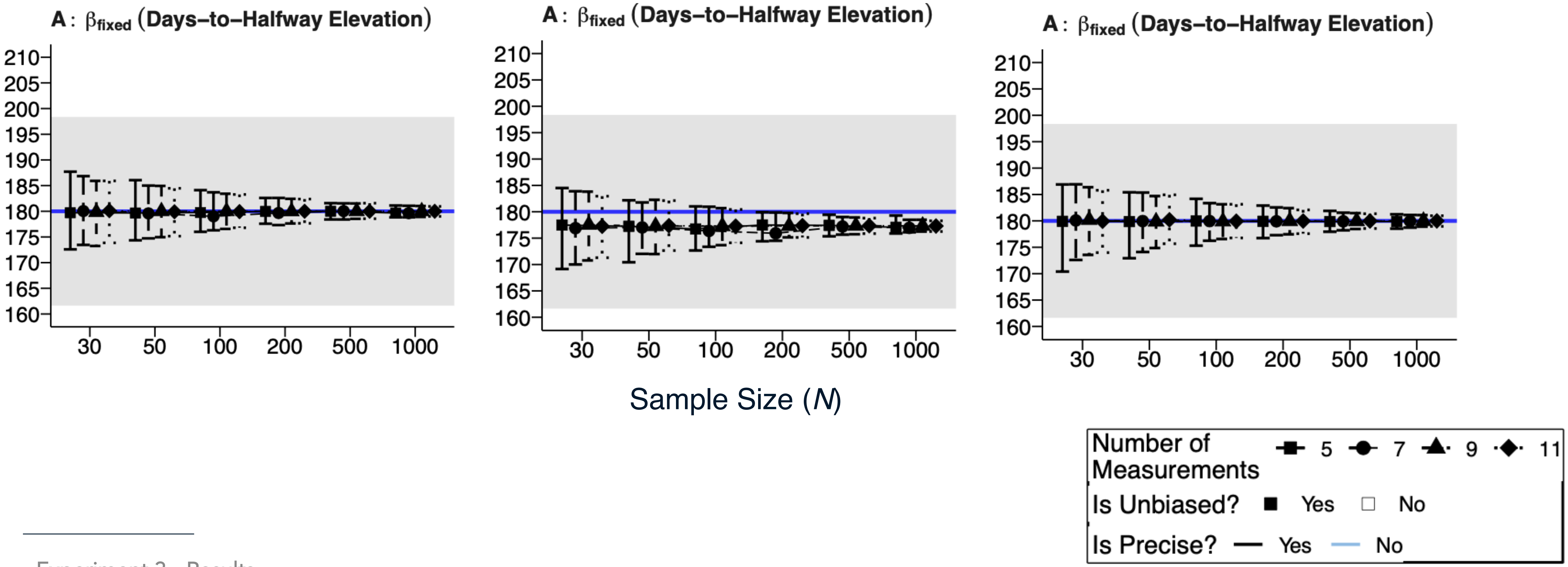
High | *Time structuredness* | *Low*

Fast | *Response rate* | *Slow*

Time structured data (immediate response rate)

Fast response rate

Slow response rate + definition variables



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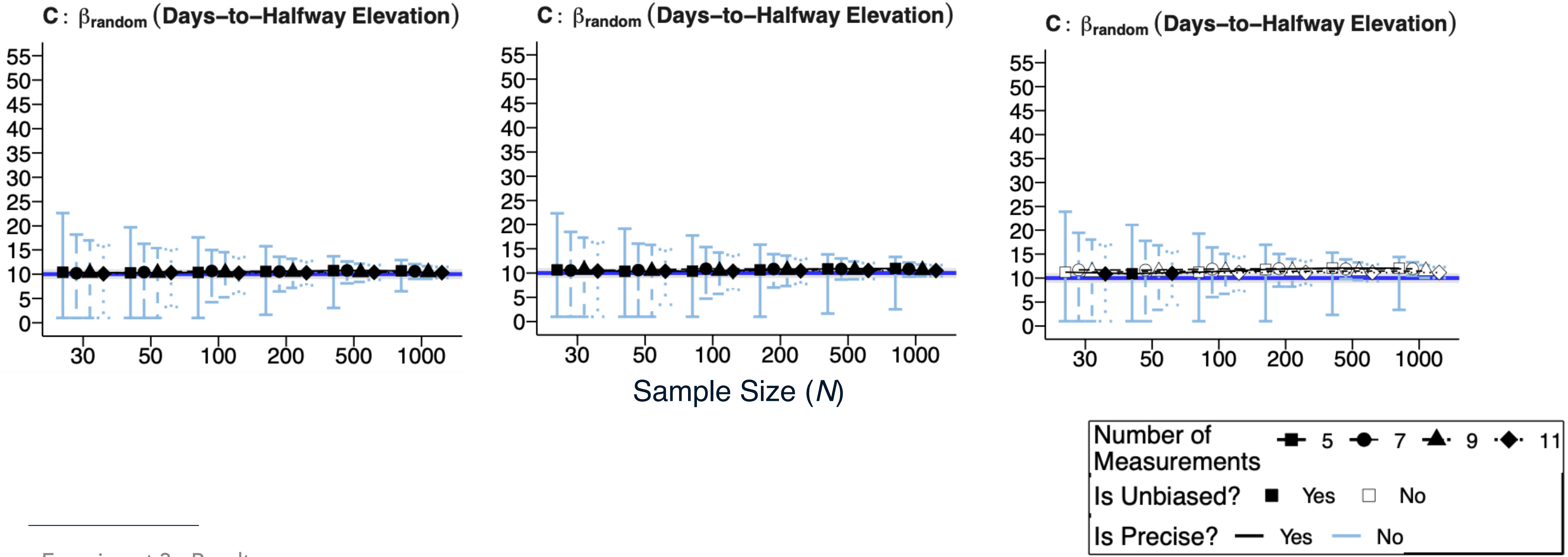

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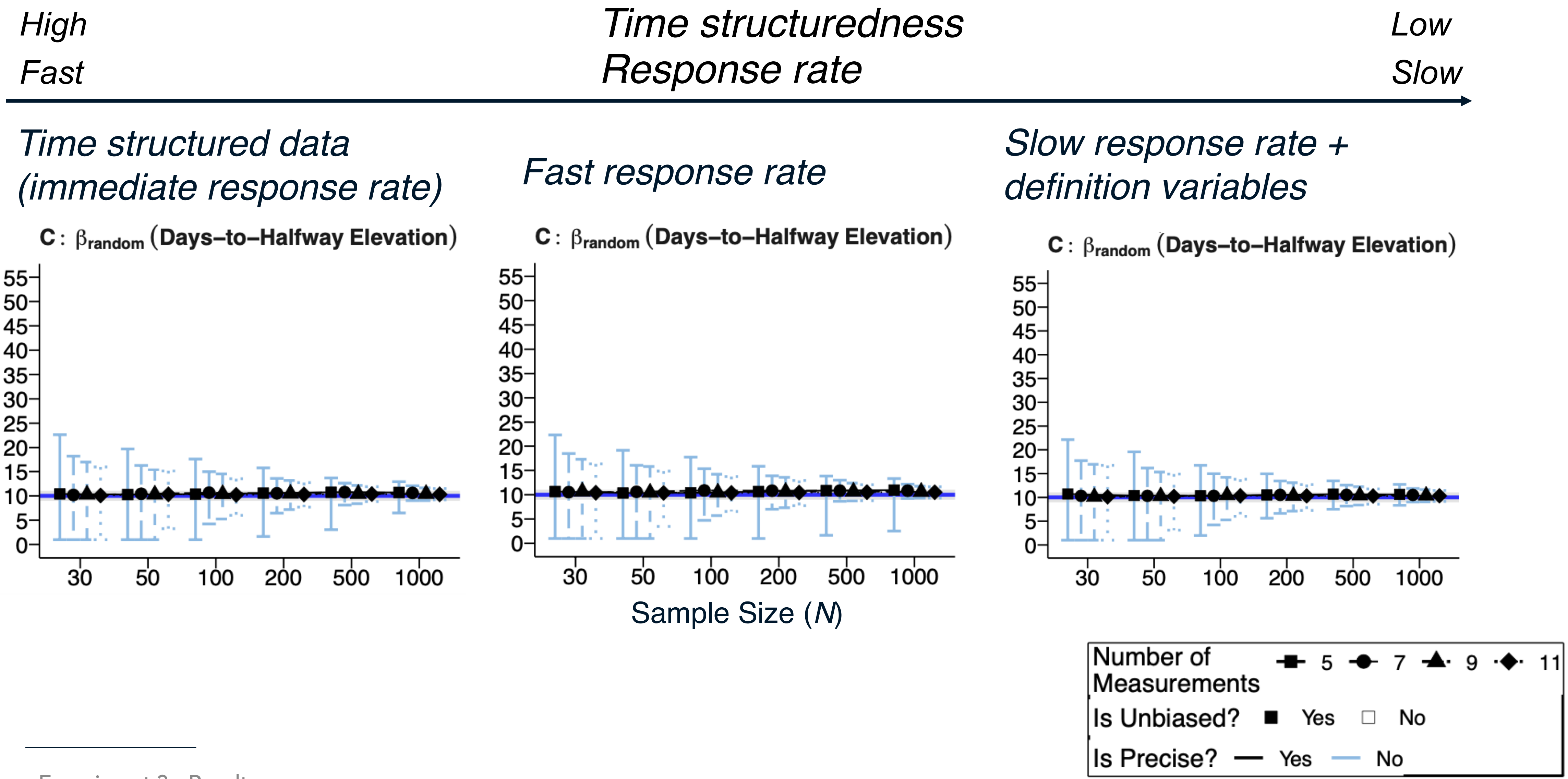

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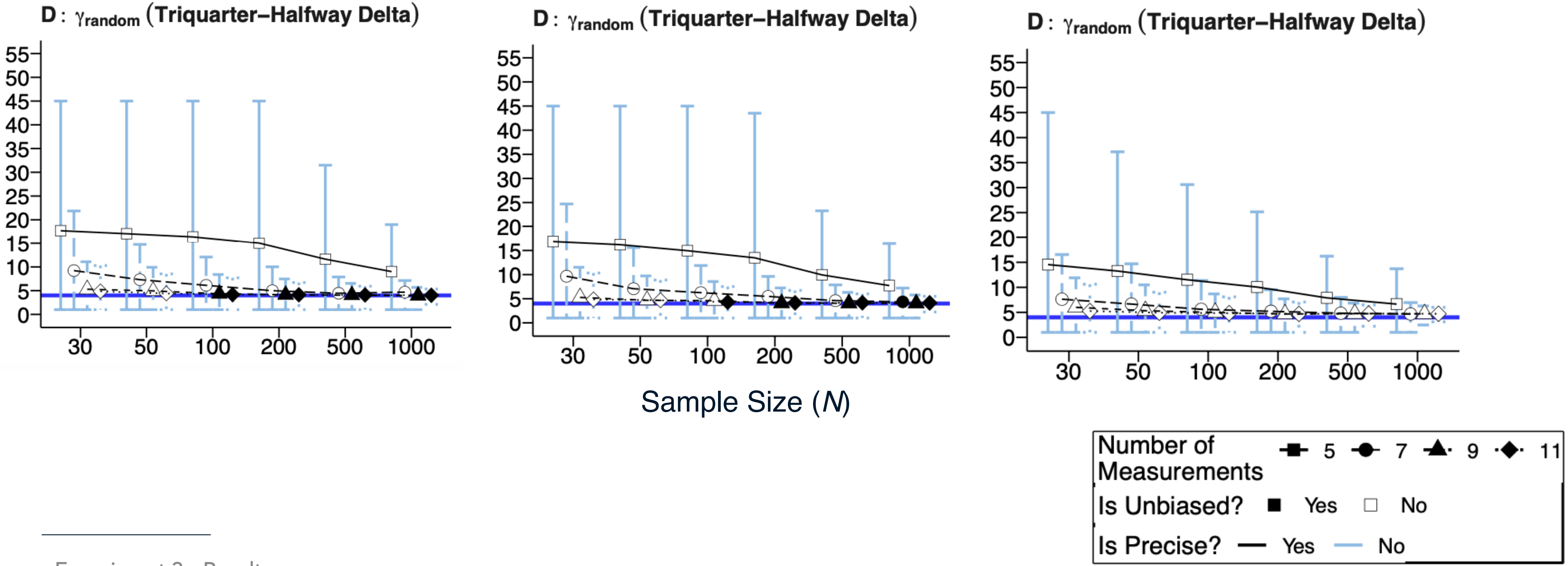

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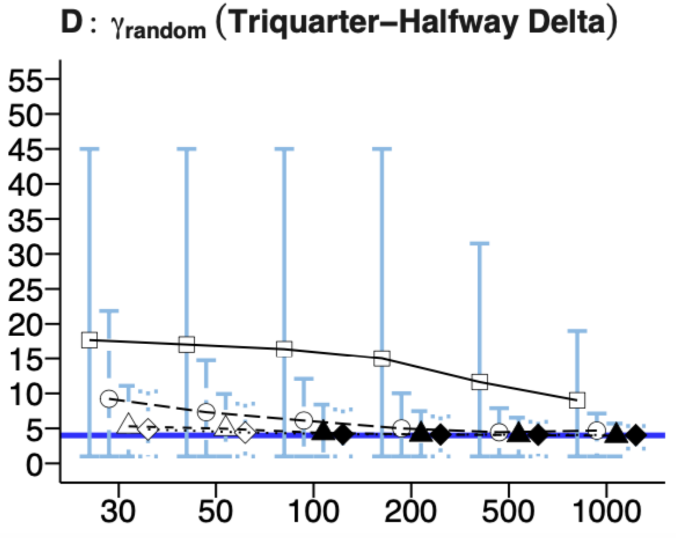
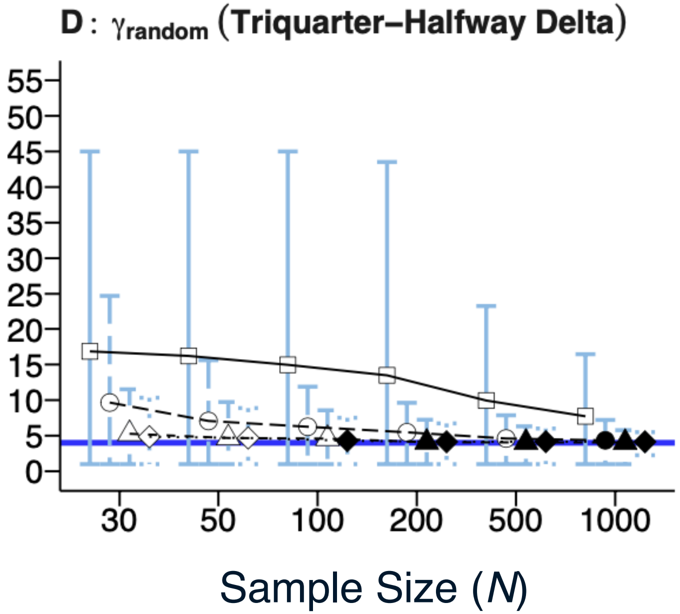
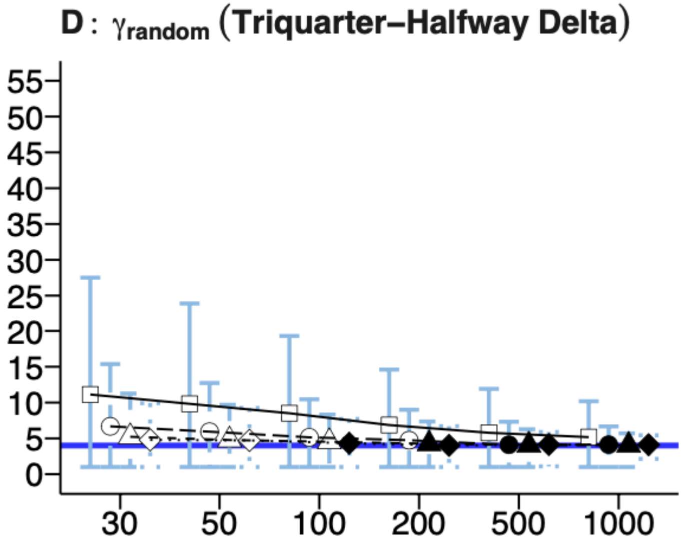
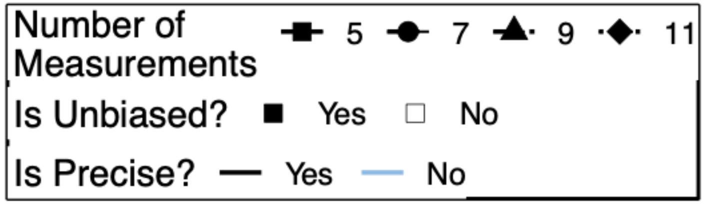


Fast response rate



Slow response rate + definition variables





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Experiment 3

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Definition variables can be used to prevent low time structuredness from increasing in bias.

If using definition variable, the largest improvements in model performance result from using either seven measurements with $N \geq 200$ or nine measurements with $N \leq 100$.

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Experiment 1

Model performance increases when measurements are placed near periods of change

When the nature of change is unknown, model performance is highest with equal spacing

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Model performance increases when measurements are placed near periods of change

When the nature of change is unknown, model performance is highest with equal spacing

Experiment 2

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Model performance increases when measurements are placed near periods of change

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The results of my experiments are the first (to my knowledge) to provide recommendations for modelling nonlinear change

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Number of measurements

Spacing of measurements

Sample size

Time structuredness

Few guidelines

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Limitations & future directions

1) Cutoff values

2) External validity

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Limitations & future directions

1) Cutoff values

2) External validity

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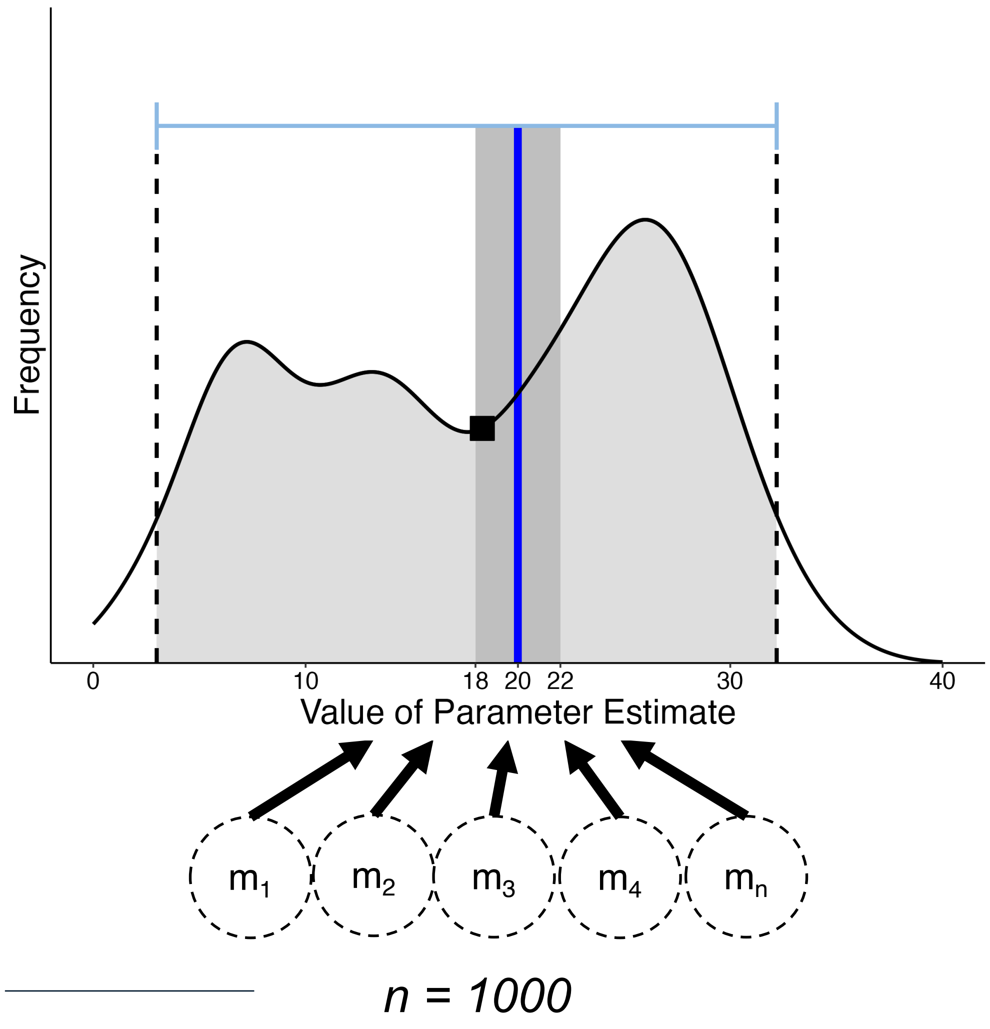
I used a percentage-based cutoff rule in my experiments



Bias: difference between average estimated value and population value

Estimates were biased if bias > 10% of population value

Precision: range of values covered by the middle 95% of estimates

Estimation was imprecise if a whisker length > 10% of population value

Muthén et al. (1997)

Percentage-based cutoff values are context dependent

A 10% increase in heart rate does not lead to the same health outcomes as a 10% increase in body temperature

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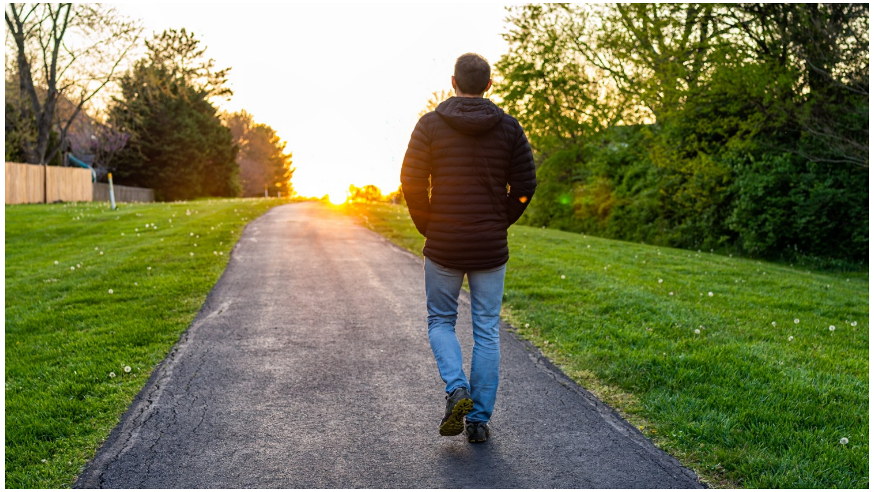
Muthén et al. (1997)

Percentage-based cutoff values are context dependent

A 10% increase in heart rate does not lead to the same health outcomes as a 10% increase in body temperature

10% increase in heart rate = 7–8 beats/minute



10% increase body temperature = 3.7℃

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Muthén et al. (1997); Nanchen (2018); Whitley & Schoene (1987); Moran & Mendal (2002)

Future research could use smallest cutoff values of interest to account for the context

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Smallest effect sizes of interest → Test for meaningful effect sizes

Lakens (2017); Lakens et al. (2018)

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Future research could use smallest cutoff values of interest to account for the context

Smallest effect sizes of interest → Test for meaningful effect sizes

Smallest cutoff values of interest → Test for meaningful changes in model performance

Lakens (2017); Lakens et al. (2018)

Limitations & future directions

1) Cutoff values

2) External validity

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The current simulation experiments generated data under ideal conditions

1) Data generation assumed 100% response rate

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Data are estimated to be missing 30% of the time, and increase over time

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McKnight et al. (2007); Newman (2003)

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2) Model assumed a constant measurement model over time (i.e., measurement invariance)

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Measurement invariance is seldom observed

3) Error variances assumed to be constant and uncorrelated over time

Error variances are likely to be heterogeneous and correlated.

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McKnight et al. (2007); Newman (2003); Mellenbergh (1989); Van De Schoot et al. (2015); Bliese & Ployhart (2002)

A gap exists between researchers and practitioners whereby research findings seldom make their way into practice

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Sanders et al. (2008); Rynes et al. (2002)

A gap exists between researchers and practitioners whereby research findings seldom make their way into practice

Poor understanding of organizational psychology among managers

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Sanders et al. (2008); Rynes et al. (2002

A gap exists between researchers and practitioners whereby research findings seldom make their way into practice

Poor understanding of organizational psychology among managers

~55% of practitioners skeptical that organizational psychology can effect positive change

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Sanders et al. (2008); Rynes et al. (2002); Spears & Bolton (2015)

One factor that may contribute to the academic-practitioner gap is the lack of specific recommendations

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Organizational theory typically specifies non-zero relations

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Edwards & Berry (2010)

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Organizational theory typically specifies non-zero relations

↓

~3% of human resource articles address problems faced by practitioners

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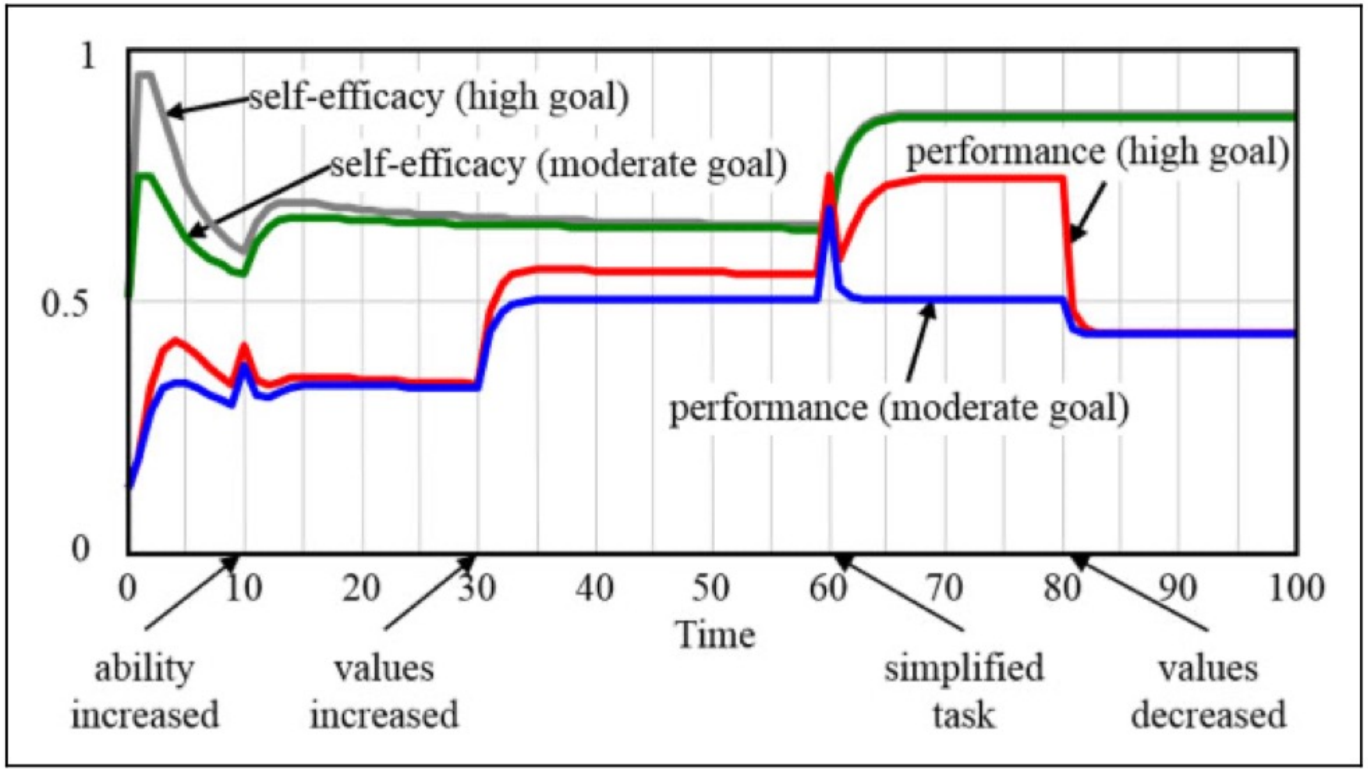
Edwards & Berry (2010); Sackett & Larson (1990)

Modelling nonlinear change could provide one avenue for to developing specific recommendations

Modelling nonlinear change could provide one avenue for to developing specific recommendations



Vancouver et al. (2020)

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