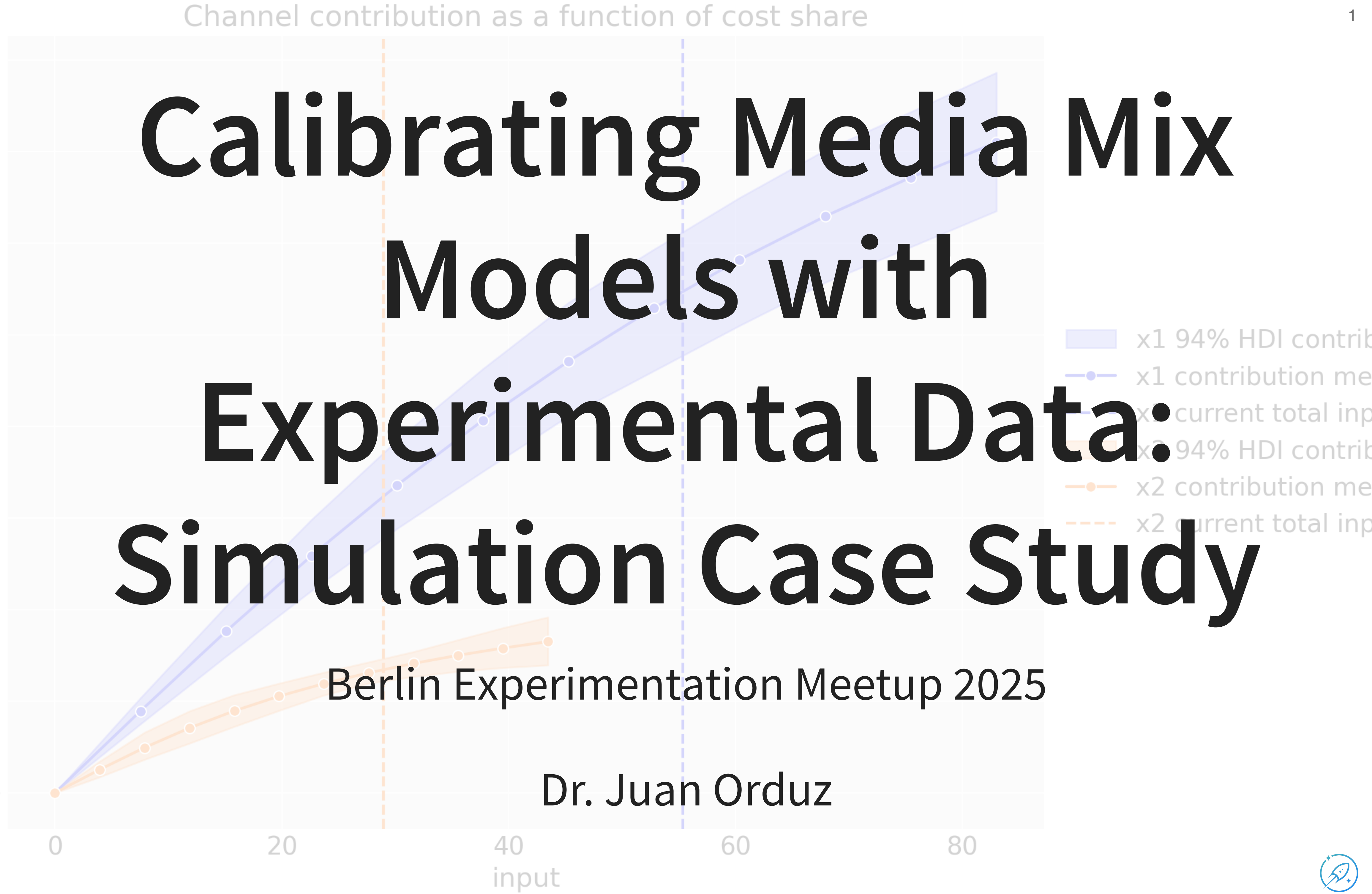
Calibrating Media Mix Models with Experimental Data: Simulation Case Study

Berlin Experimentation Meetup 2025

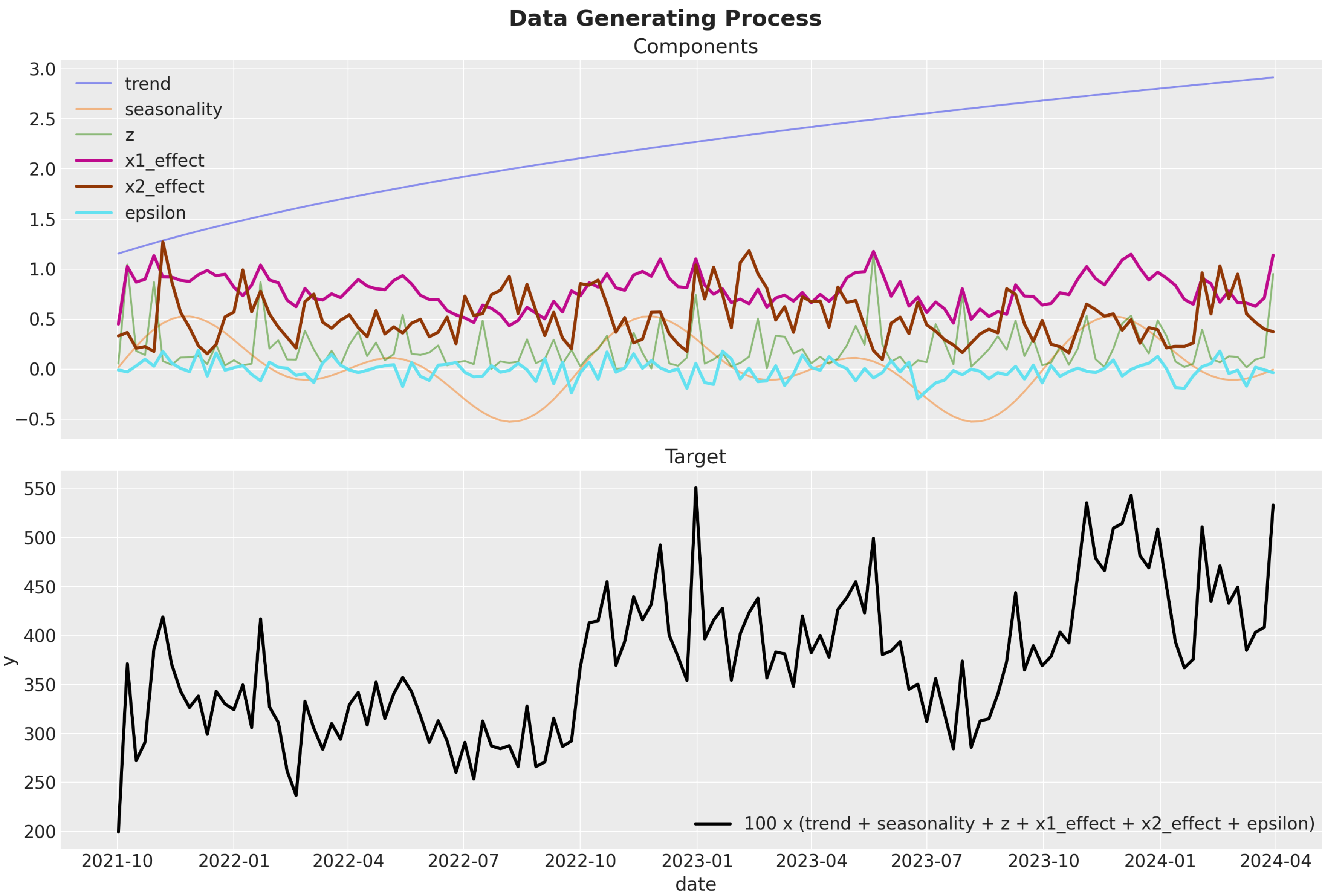
Dr. Juan Orduz



Outline

1. **What is Media Mix Modeling (MMM)?**
   - Regression Model
   - Adstock Transformation
   - Saturation Transformation
   - Bayesian MMMs (Challenges and Opportunities)
2. **Simulation Case Study**
   - Simulation Setup
   - Channels Contributions
   - ROAS Estimates
3. **ROAS Re-parametrization**
4. **Lift Test Calibration**

What is Media Mix Modeling (MMM)?



MMM as a Regression Model

$$y_t = b_t + \sum_{m=1}^{M} \beta_{m,t} f(x_{m,t}) + \sum_{c=1}^{C} \gamma_c z_{c,t} + \varepsilon_t,$$

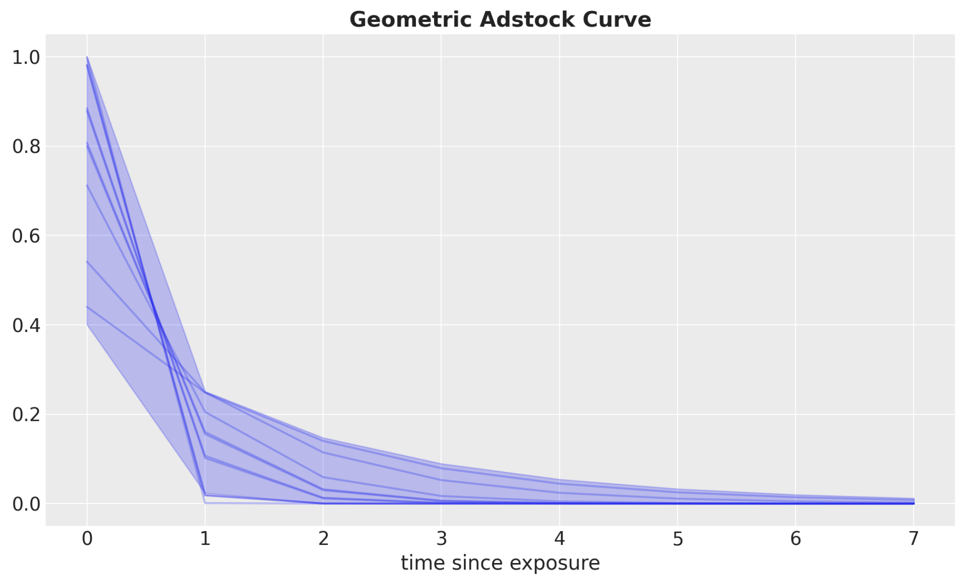
- y_t: Target variable at time t (e.g. sales, conversions, etc.)
- b_t: Baseline sales at time t
- $\beta_{m,t}$: Effect of media m on sales at time t
- $f(x_{m,t})$: Transformation of media m at time t
- γ_c: Effect of control variables $z_{c,t}$ on sales
- ε_t: Error term

Adstock Effect

The adstock effect captures the **carryover** of advertising - the idea that the impact of advertising persists and decays over time rather than being instantaneous.

$$\text{adstock}(x_{m,t}; \alpha, T) = x_{m,t} + \alpha \sum_{j=1}^{T} x_{m,t-j}$$

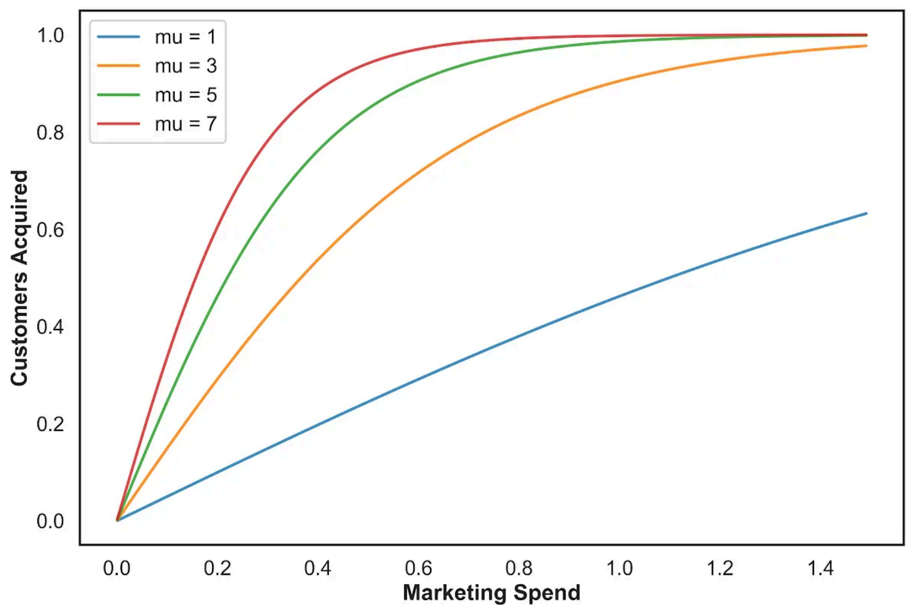
for $\alpha \in [0, 1]$ and T the number of periods.



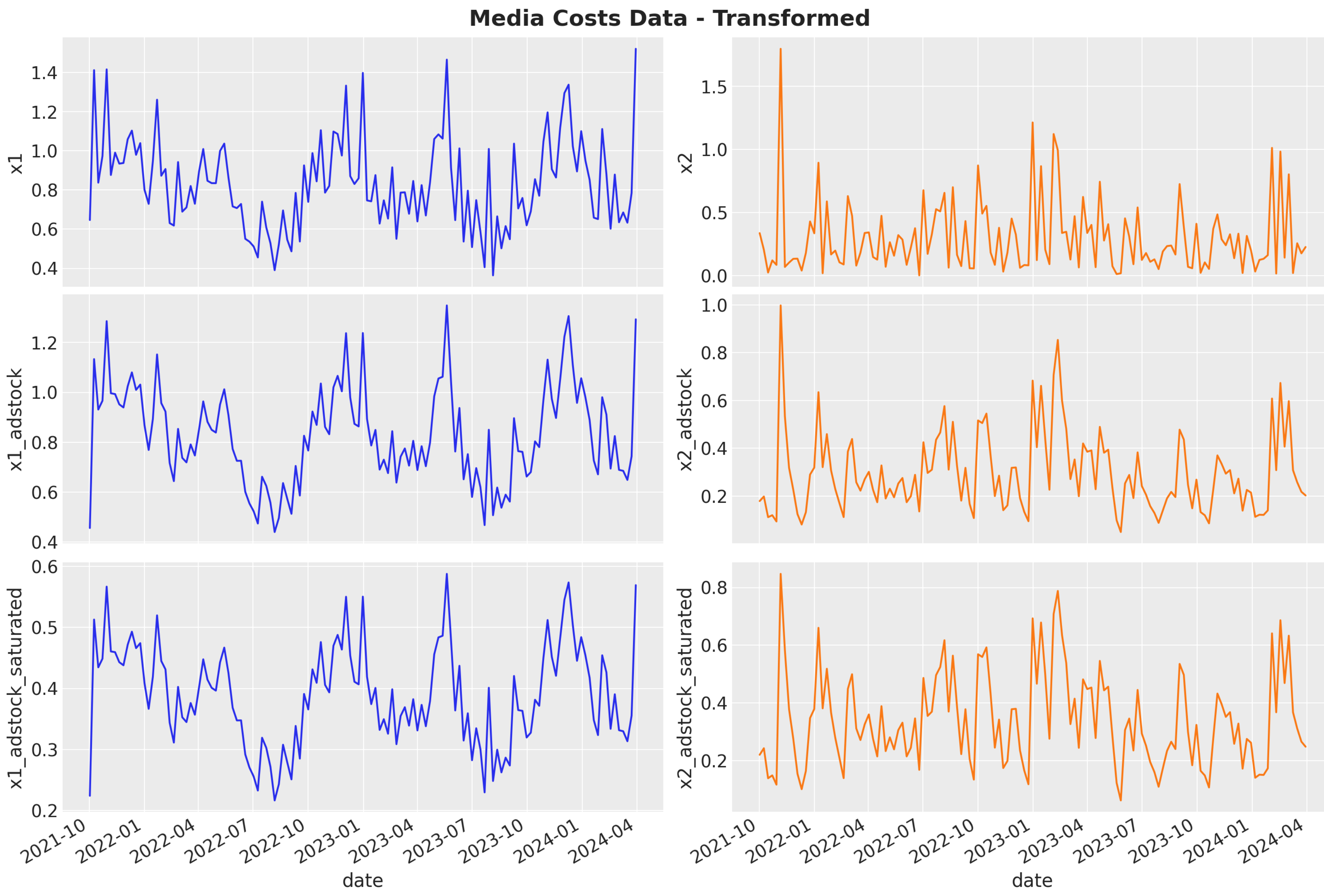
Saturation Effect

The saturation effect captures the idea that the impact of advertising diminishes as the media budget increases.

$$\text{saturation}(x_{m,t}; \lambda) = \frac{1 - \exp(-\lambda x_{m,t})}{1 + \exp(-\lambda x_{m,t})}$$



Media Transformations



Why Bayesian MMMs?

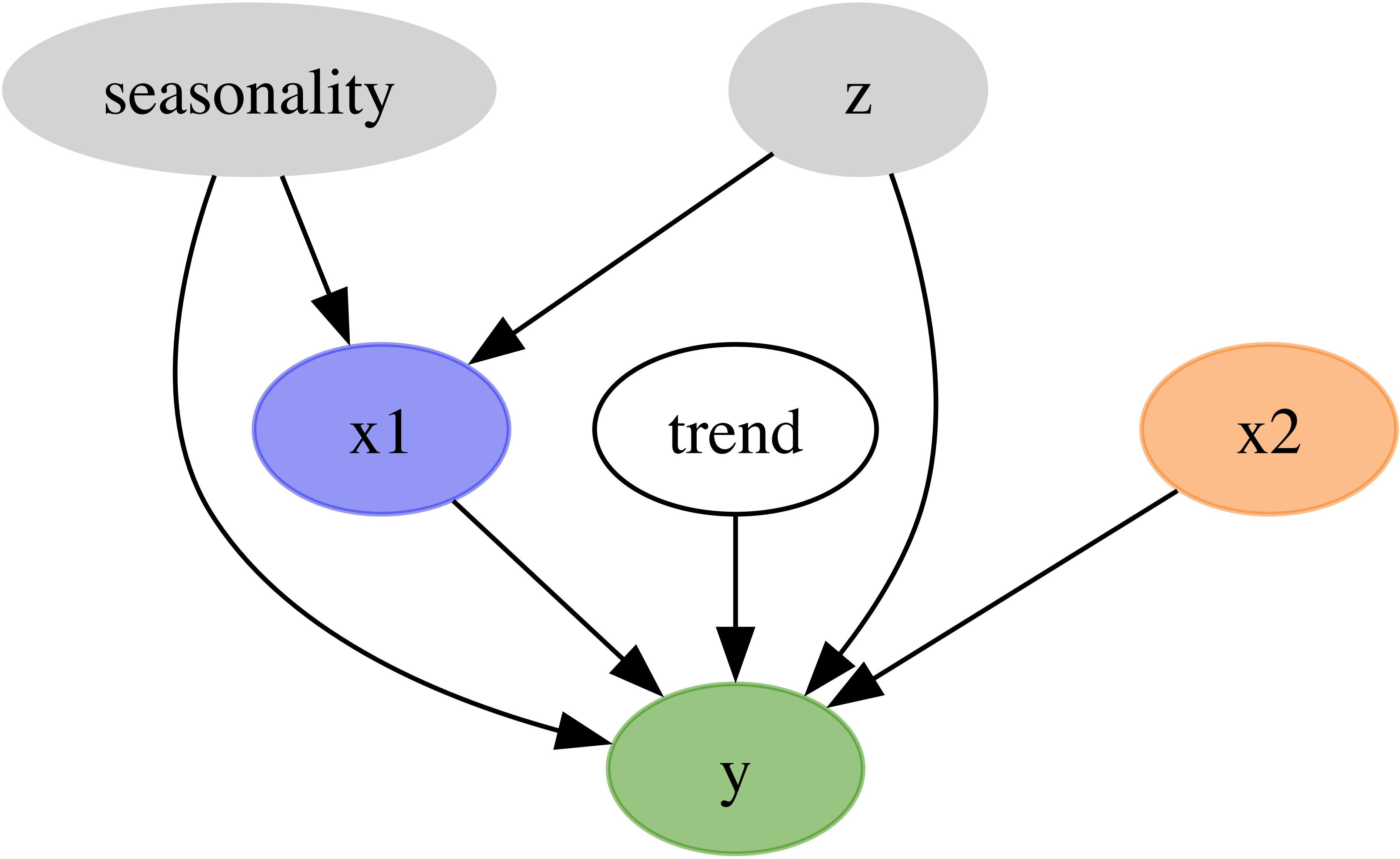
Some MMM Challenges

- Limited data (typically 2-3 years of data, sometimes weekly granularity).
- Media variables are generally very correlated.
- Unobserved confounders (e.g. competitors investments).

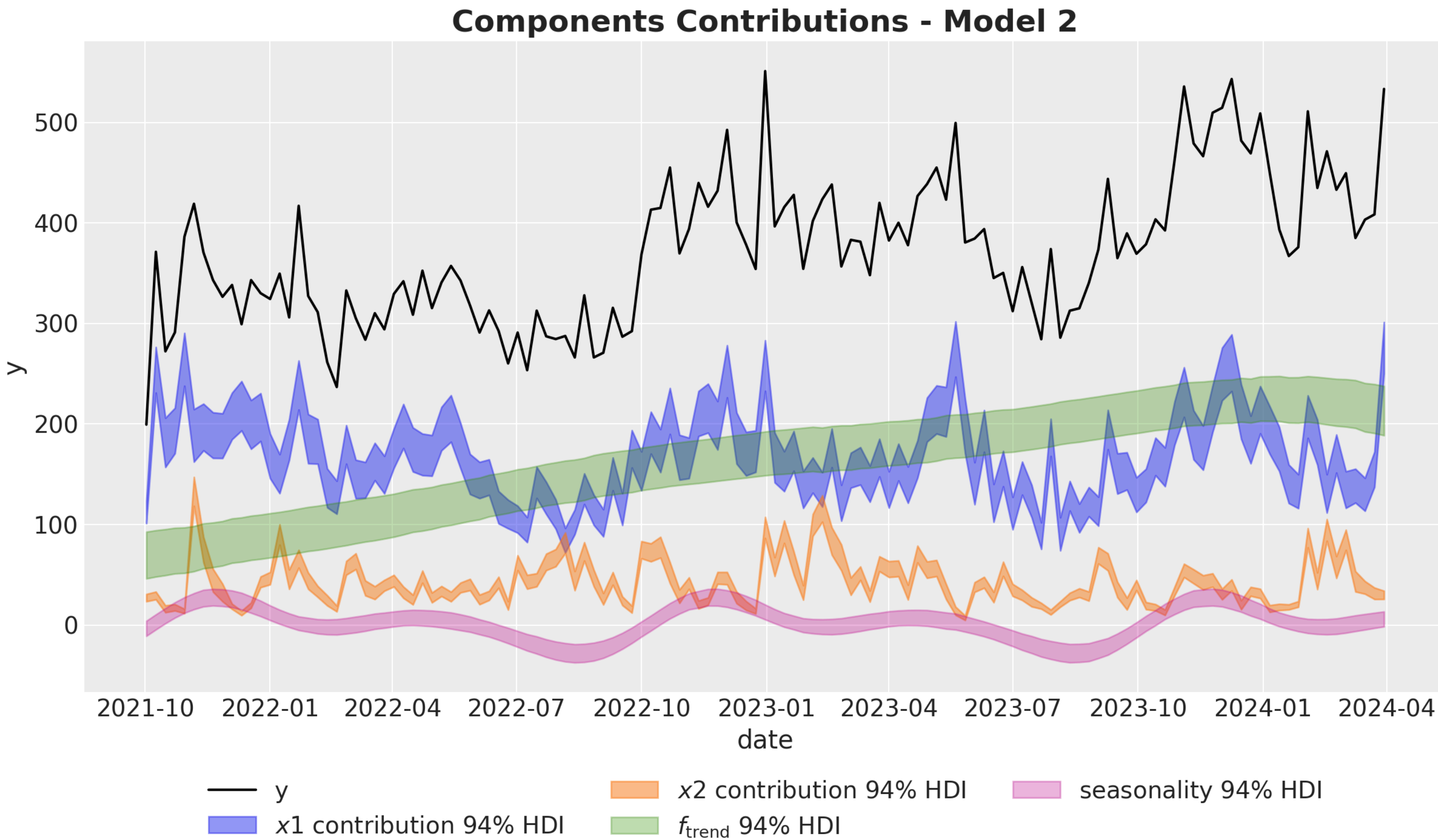
Bayesian MMMs

- Uncertainty quantification.
- Domain knowledge through priors.
- **Lift test calibration (e.g. geo-tests or switch-back experiments).**
- Time-varying parameters with Bayesian regularization (e.g. strong priors or hierarchies).
- Risk-based budget optimization.

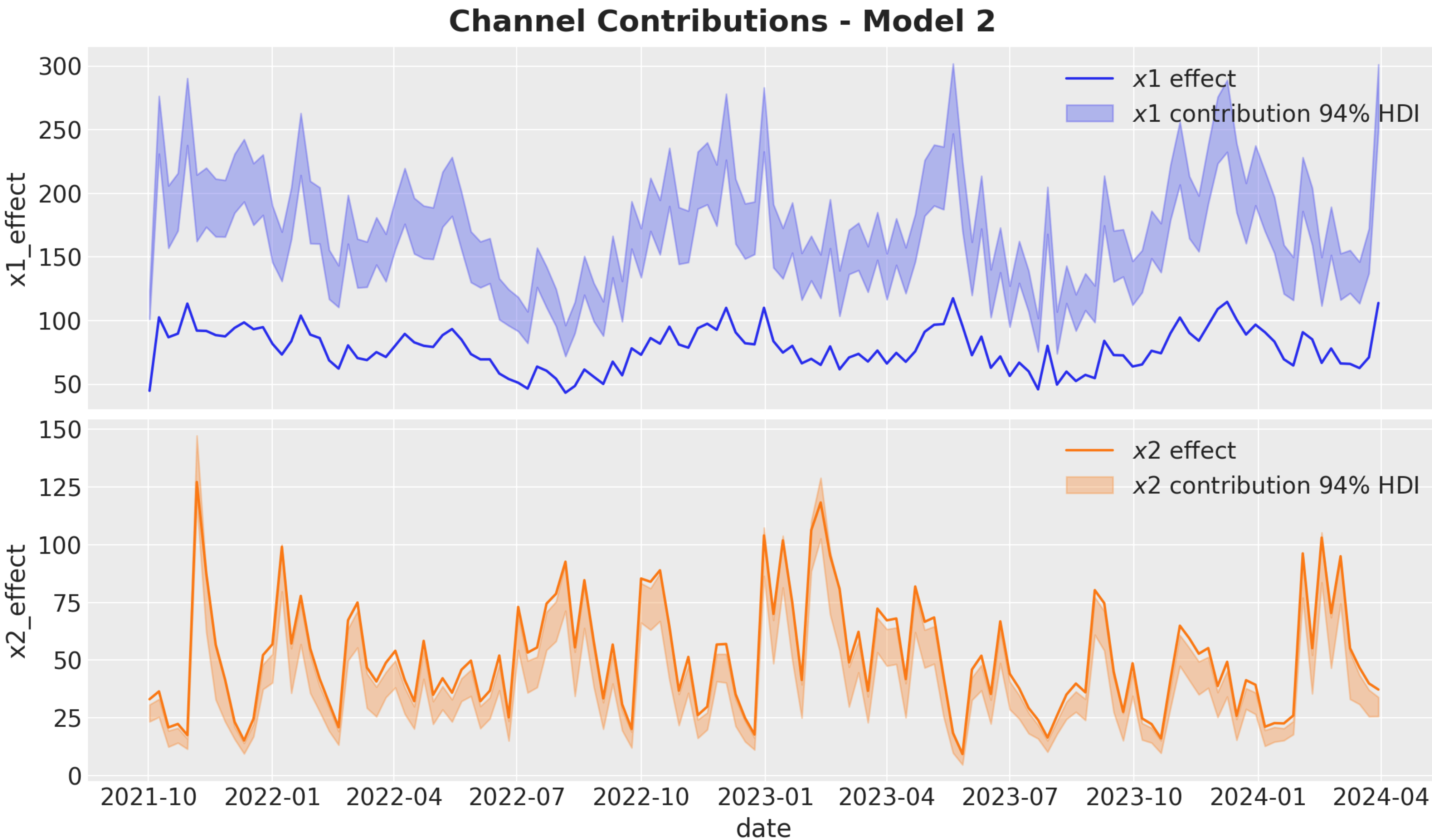
MMM as a Causal Model



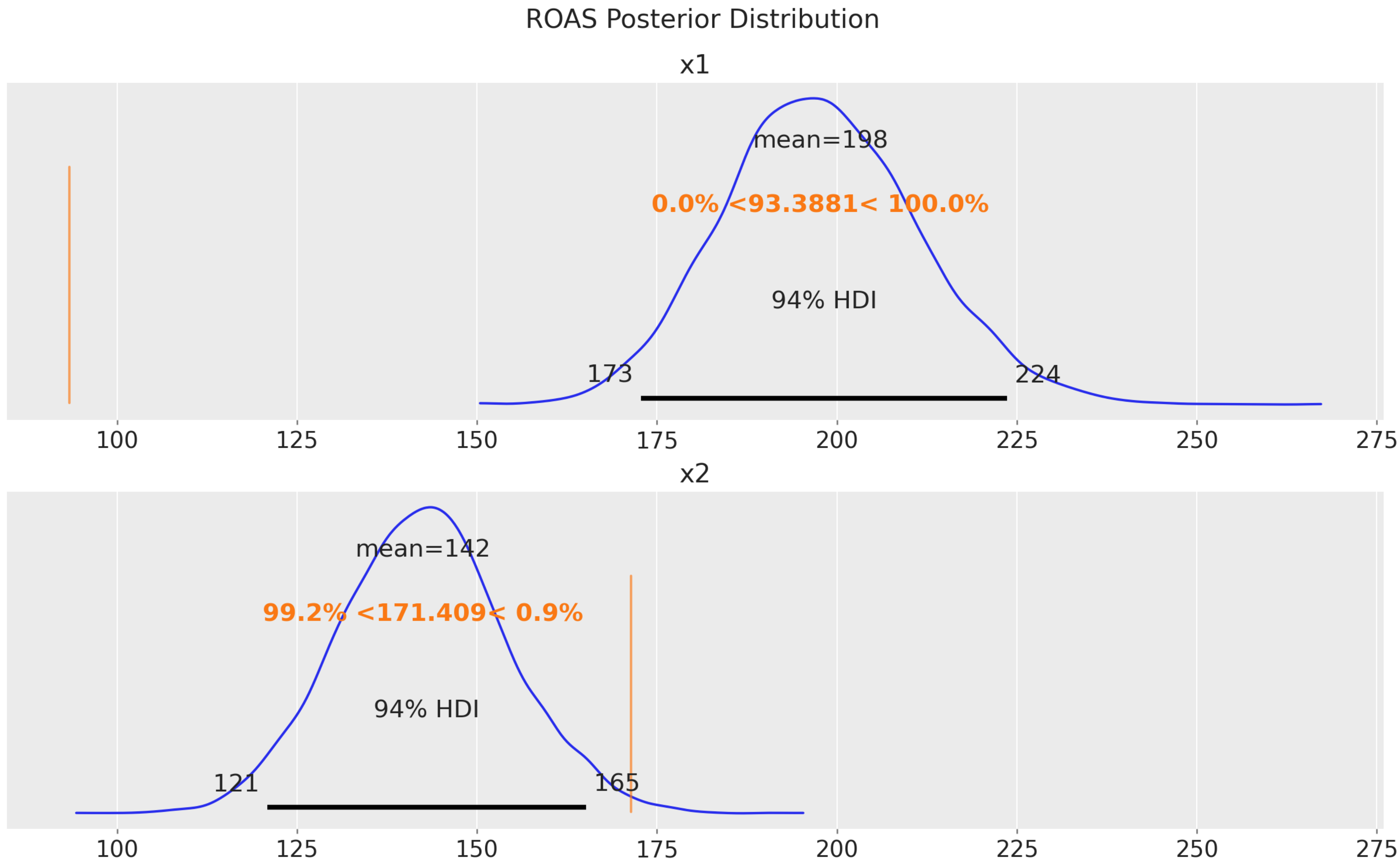
Attribution Decomposition



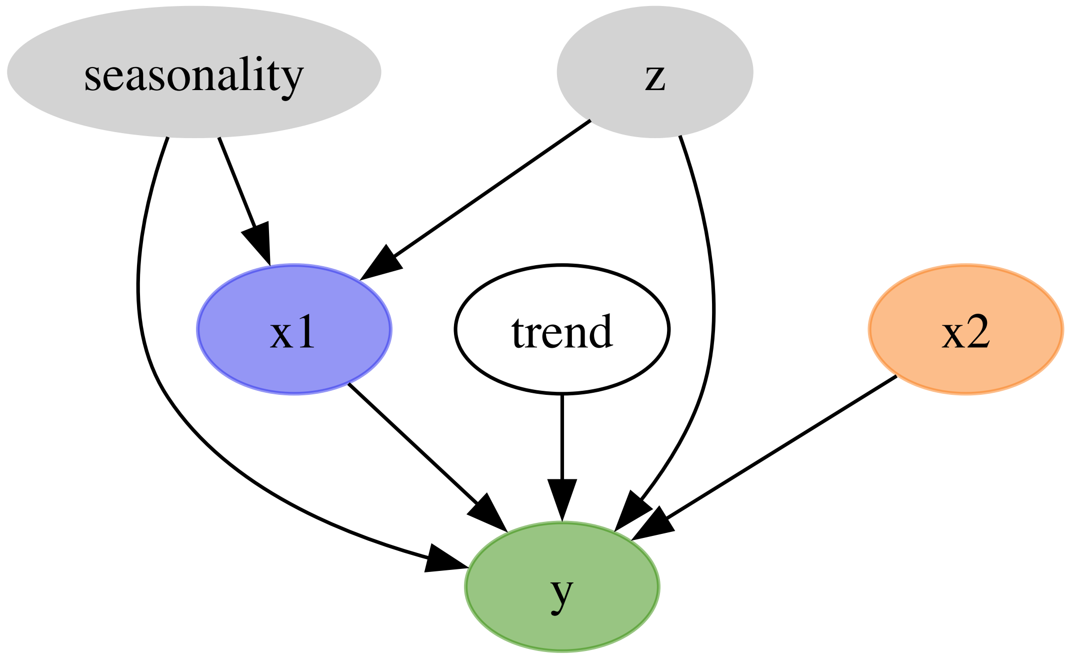
Channels Contributions over Time



Return on Ad Spend (ROAS) - Biased



Lift Test Calibration - Why?



Unobserved confounders can bias the ROAS estimates and lead to wrong marketing strategies!

- ROAS re-parametrization (Google).
- Additional likelihood for lift tests (PyMC-Labs).

ROAS Re-parametrization

Formulation

BMMM (Jin et al. [2017]) is modeled by the following generic equation,

$$y_t = \tau + \sum_{m=1}^{M} \beta_m Hill(Adstock(x^*_{t,m}, \alpha_m, L), K_m, S_m) + \sum_{c=1}^{C} \gamma_c z_{t,c} + \epsilon_t \qquad (14)$$

Following the same reparameterization process, β_m can be written as,

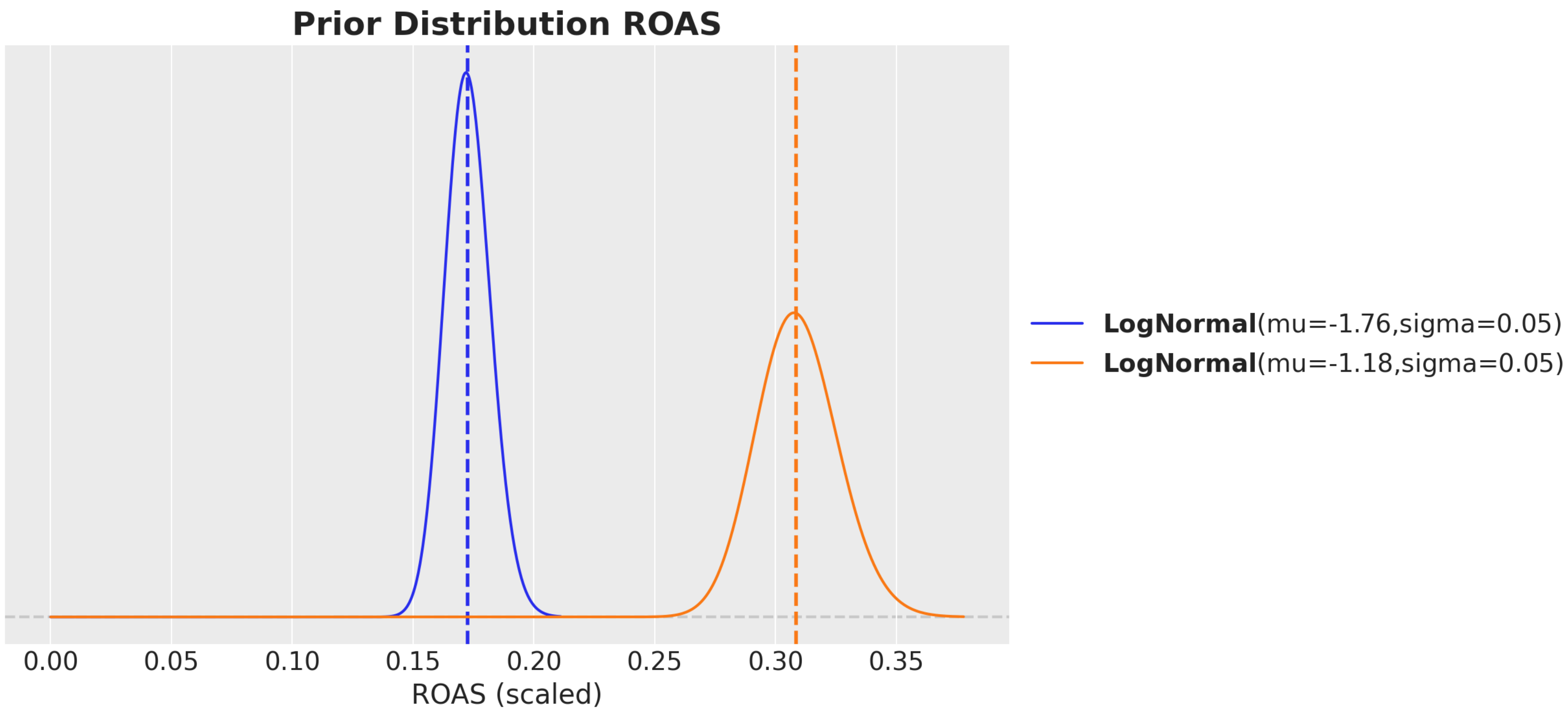
$$\beta_m = \frac{\sum_{T_0 \leq t \leq T_1} C_{t,m} ROAS_m}{\sum_{T_0 \leq t \leq T_1 + L} (Hill(Adstock(x^*_{t,m}, \alpha_m, L), K_m, S_m) - Hill(Adstock(\tilde{x}^*_{t,m}, \alpha_m, L), K_m, S_m))}$$
$$:= H^{'}(ROAS_m, K_m, S_m, \alpha_m),$$

As a result, BMMM can also be reparameterized with $ROAS_m$ as a parameter instead of β_m, as in

$$y_t = \tau + \sum_{m=1}^{M} H^{'}(ROAS_m, K_m, S_m, \alpha_m) Hill(Adstock(x^*_{t,m}, \alpha_m, L), K_m, S_m) + \sum_{c=1}^{C} \gamma_c z_{t,c} + \epsilon_t \qquad (15)$$

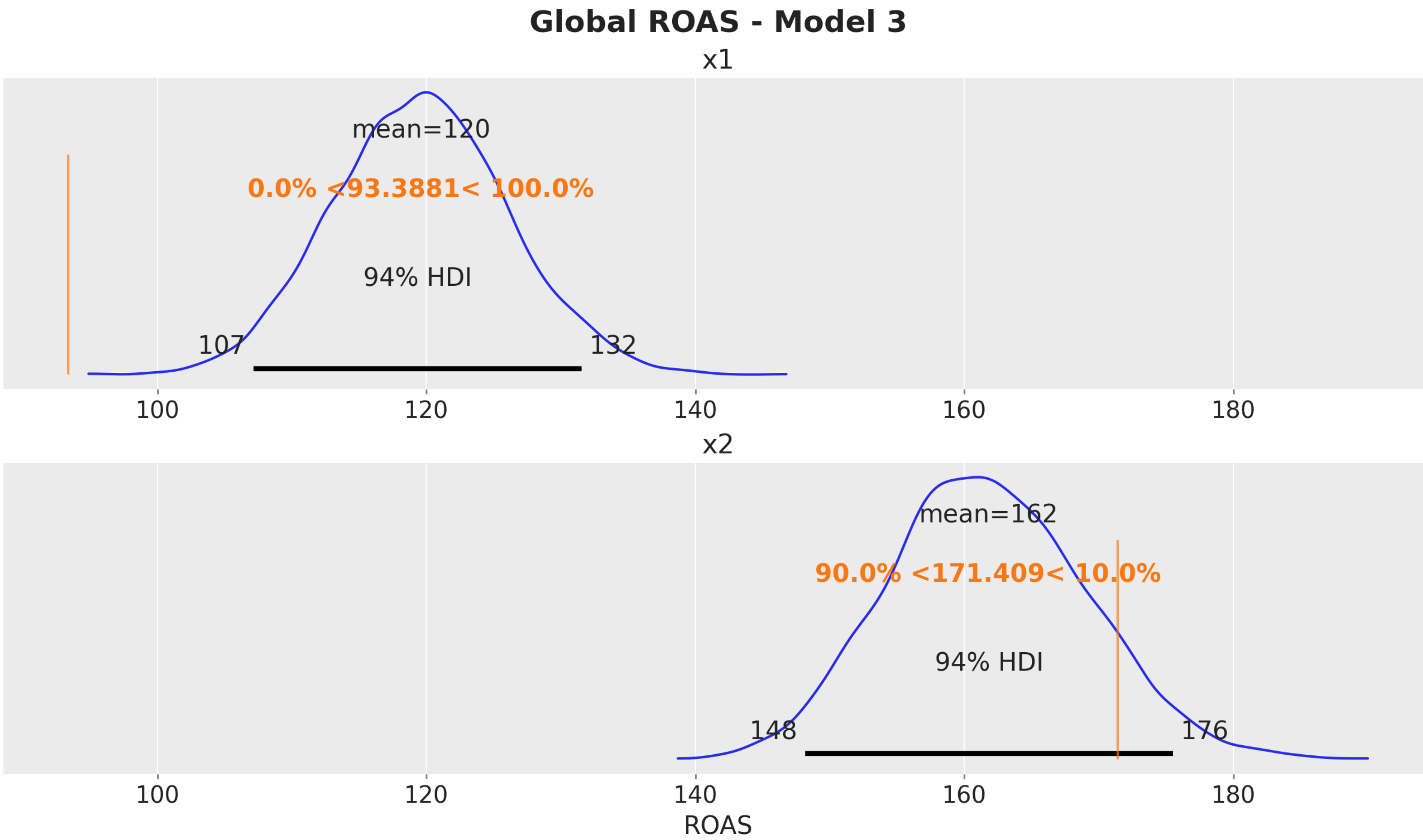
ROAS Re-parametrization

ROAS Priors



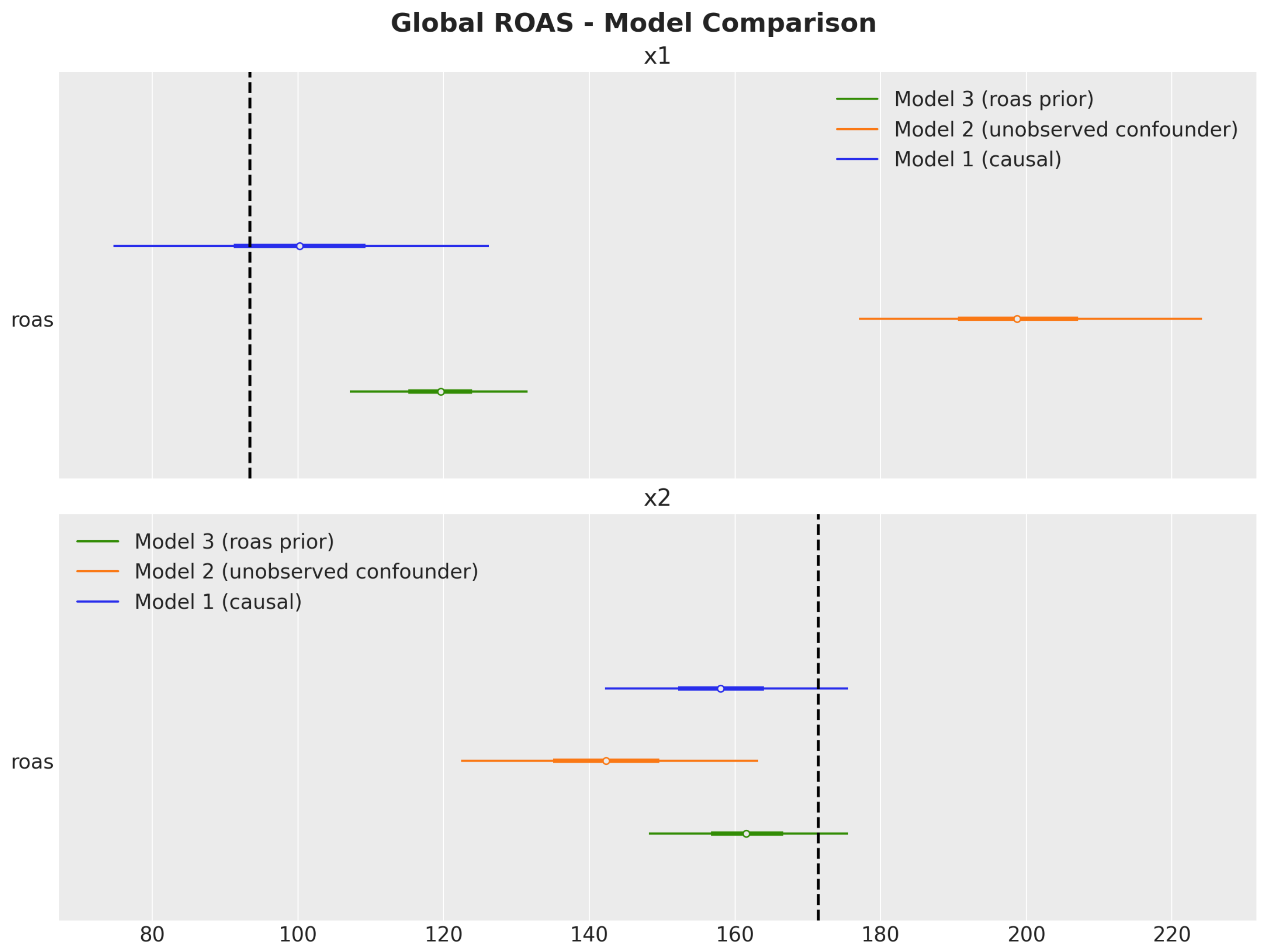
ROAS Re-parametrization

ROAS Posterior



ROAS Re-parametrization

Model Comparison

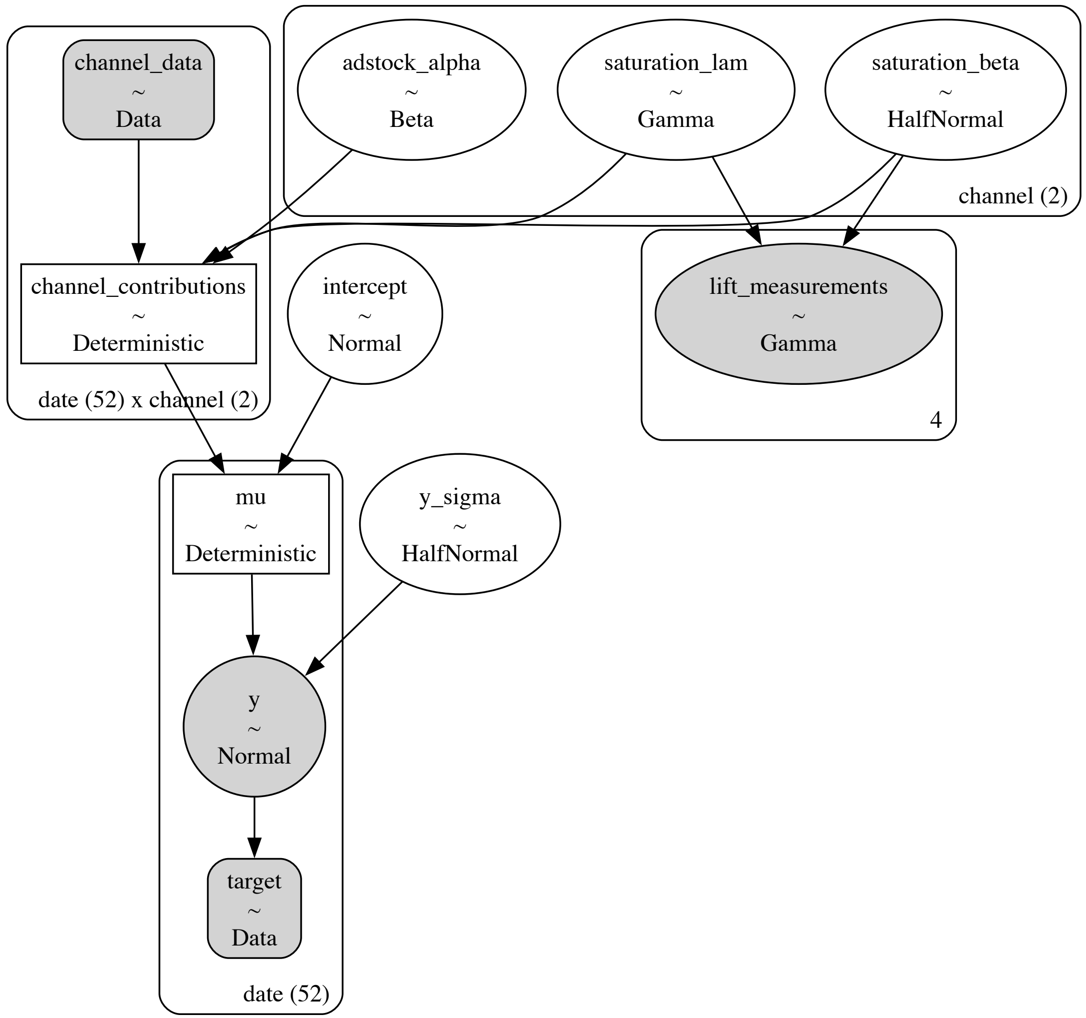


Lift Test Calibration

Saturation Curves

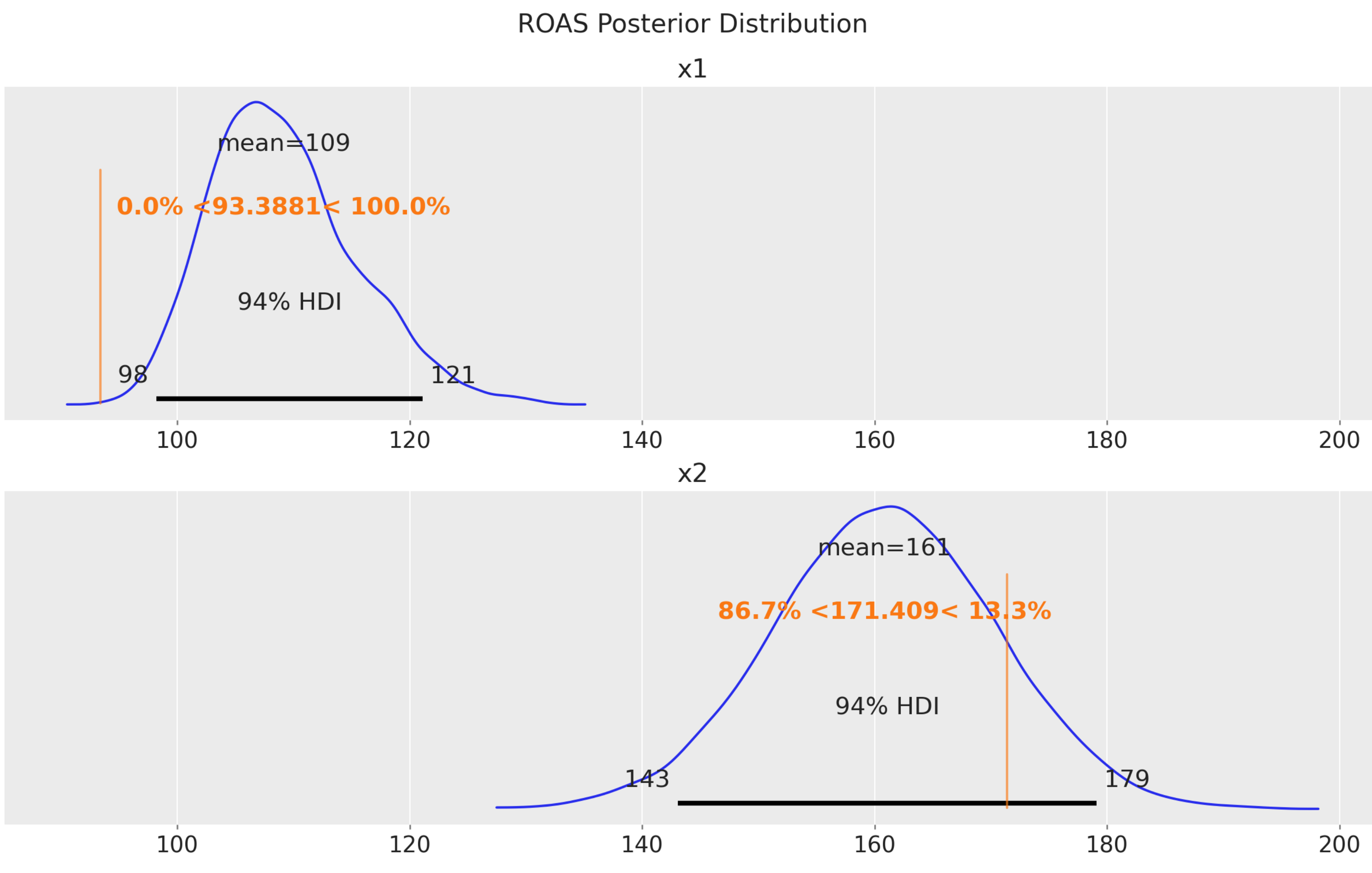
Lift Test Calibration

Additional Likelihood



Lift Test Calibration

ROAS Posterior



PyMC-Marketing

> Bayesian marketing toolbox in PyMC. Media Mix (MMM), customer lifetime value (CLV), buy-till-you-die (BTYD)

References

ROAS Re-parametrization

- Media Mix Model Calibration With Bayesian Priors
- Media Mix Model and Experimental Calibration: A Simulation Study
- Google Meridian: https://github.com/google/meridian

Additional Likelihood

- PyMC-Marketing: Lift Test Calibration
- Case Study: Unobserved Confounders, ROAS and Lift Tests
- PyMC-Marketing: https://github.com/pymc-labs/pymc-marketing

Marketing Experimentation

- Wolt Tech Talks: Offline Campaign Analysis Measurement
- Google: The MMM Handbook

Thank You!

juan.orduz@pymc-labs.com