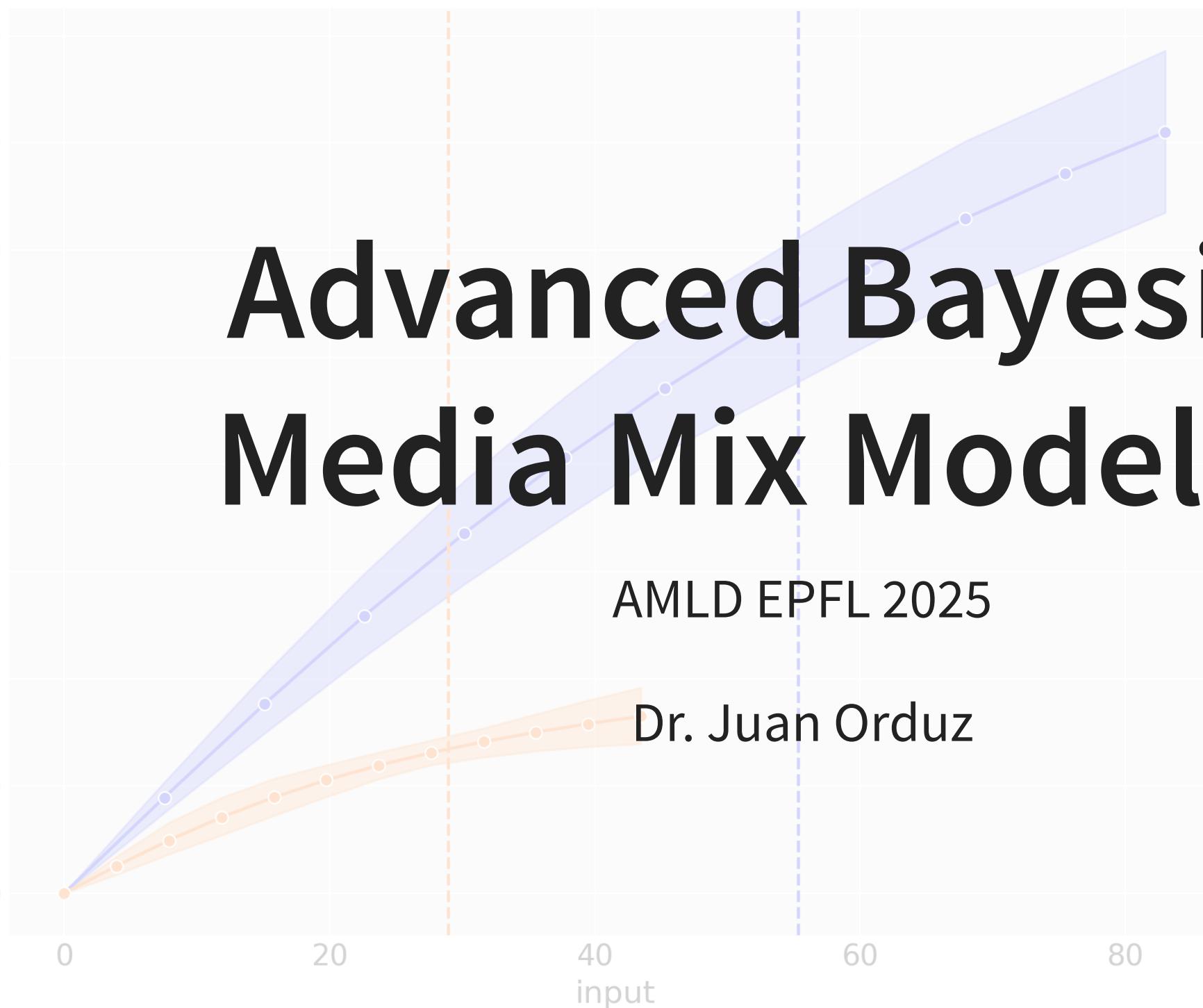


Advanced Bayesian Media Mix Modeling

AMLD EPFL 2025

Dr. Juan Orduz



Outline

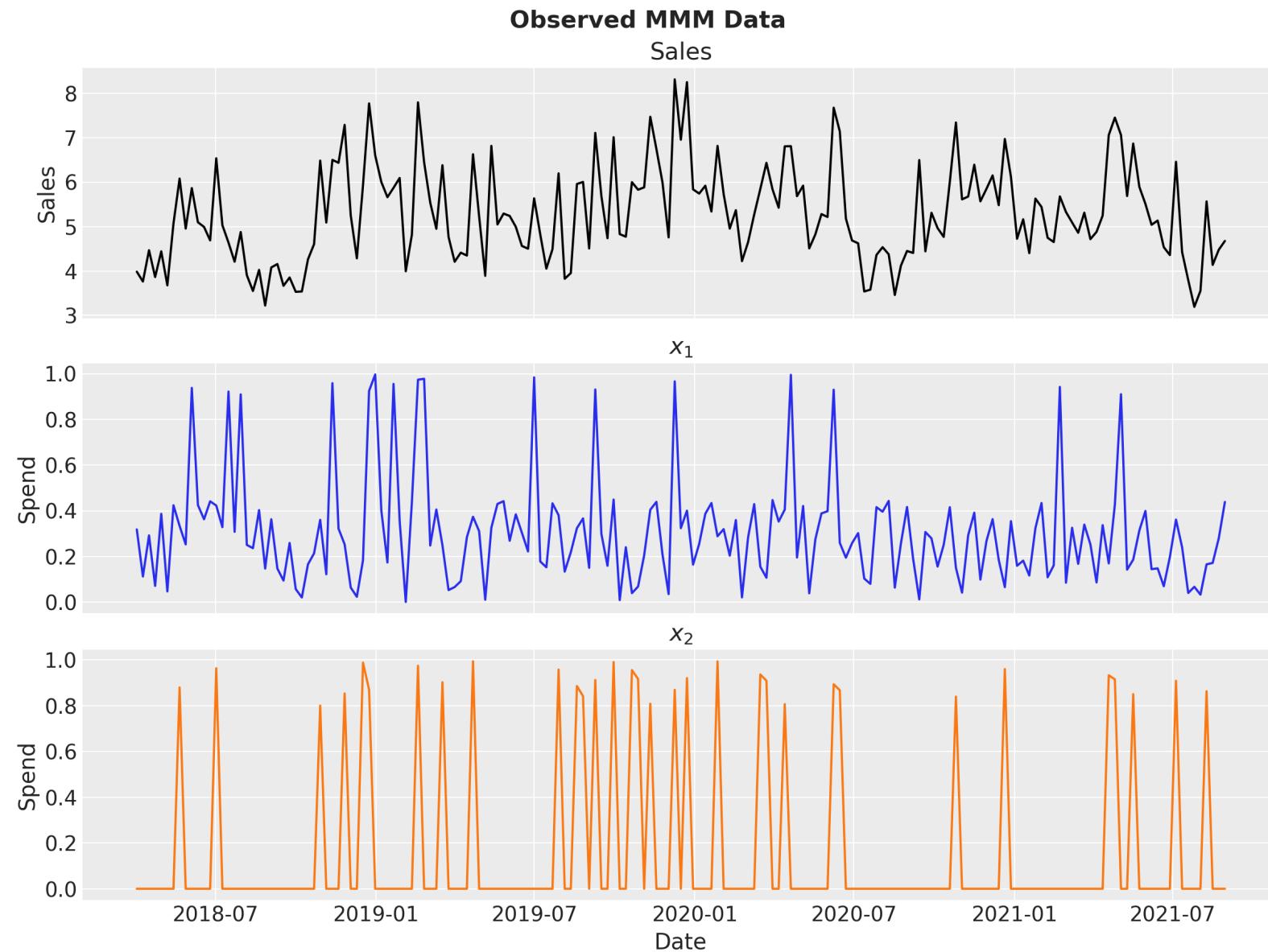
1. What is Media Mix Modeling (MMM)?
2. Media Transformations: Adstock and Saturation
3. **PyMC-Marketing**: A Python Library for Bayesian Media Mix Modeling and Customer Lifetime Value

Advanced Topics:

- Out-of-sample forecasting
- Budget Optimization and Simulations
- Time-varying parameters (baseline and media effects)
- Lift test calibration through custom likelihoods



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

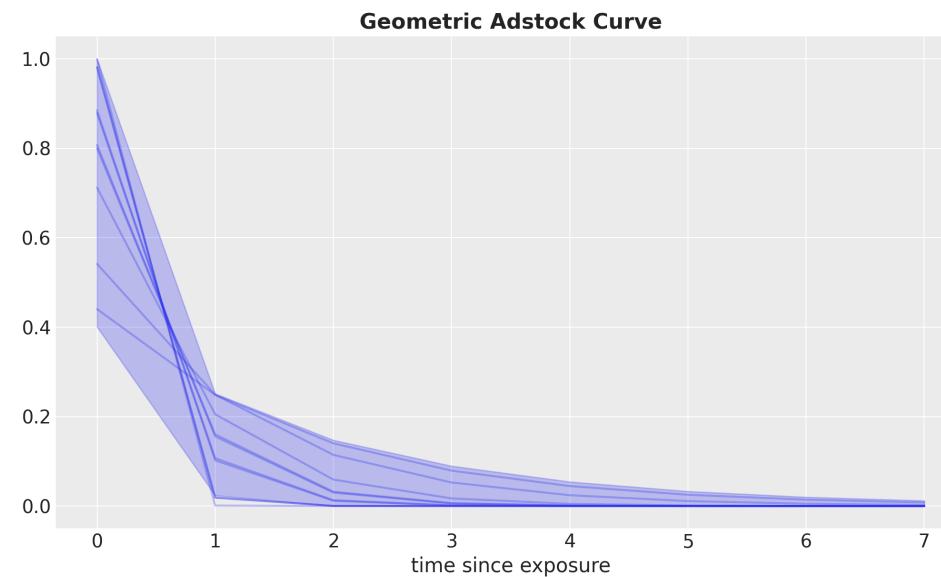


Adstock Effect

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

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

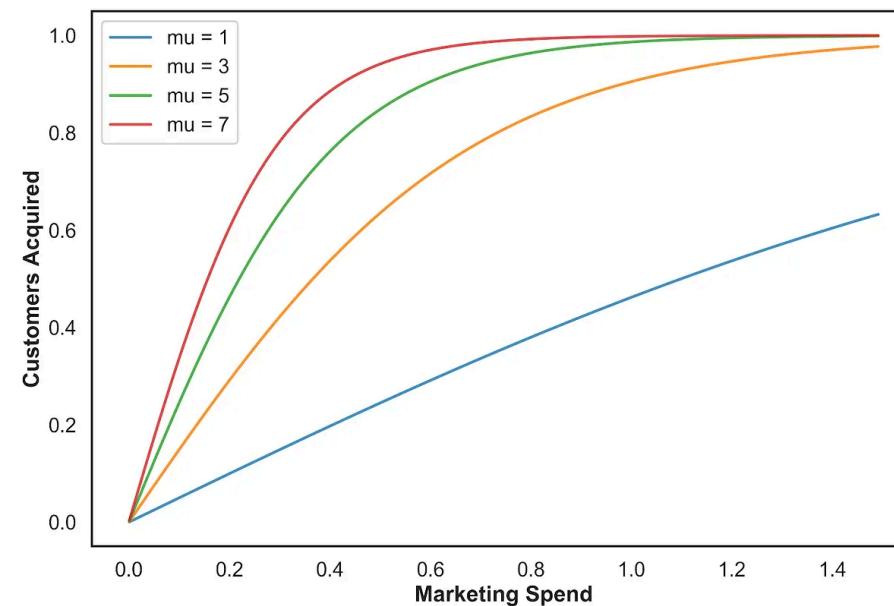
for $\alpha \in [0, 1]$ and T the number of periods.



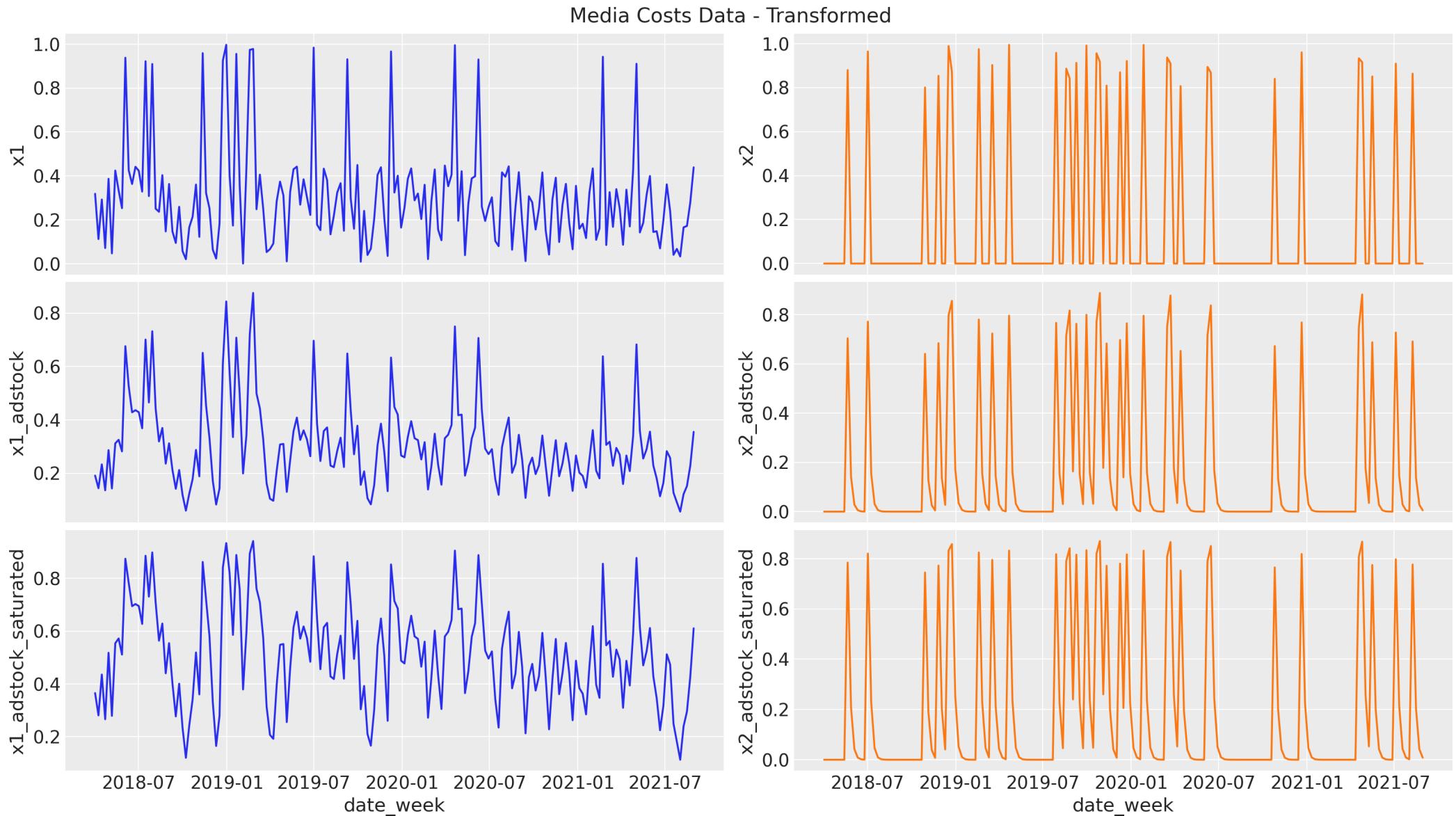
Saturation Effect

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

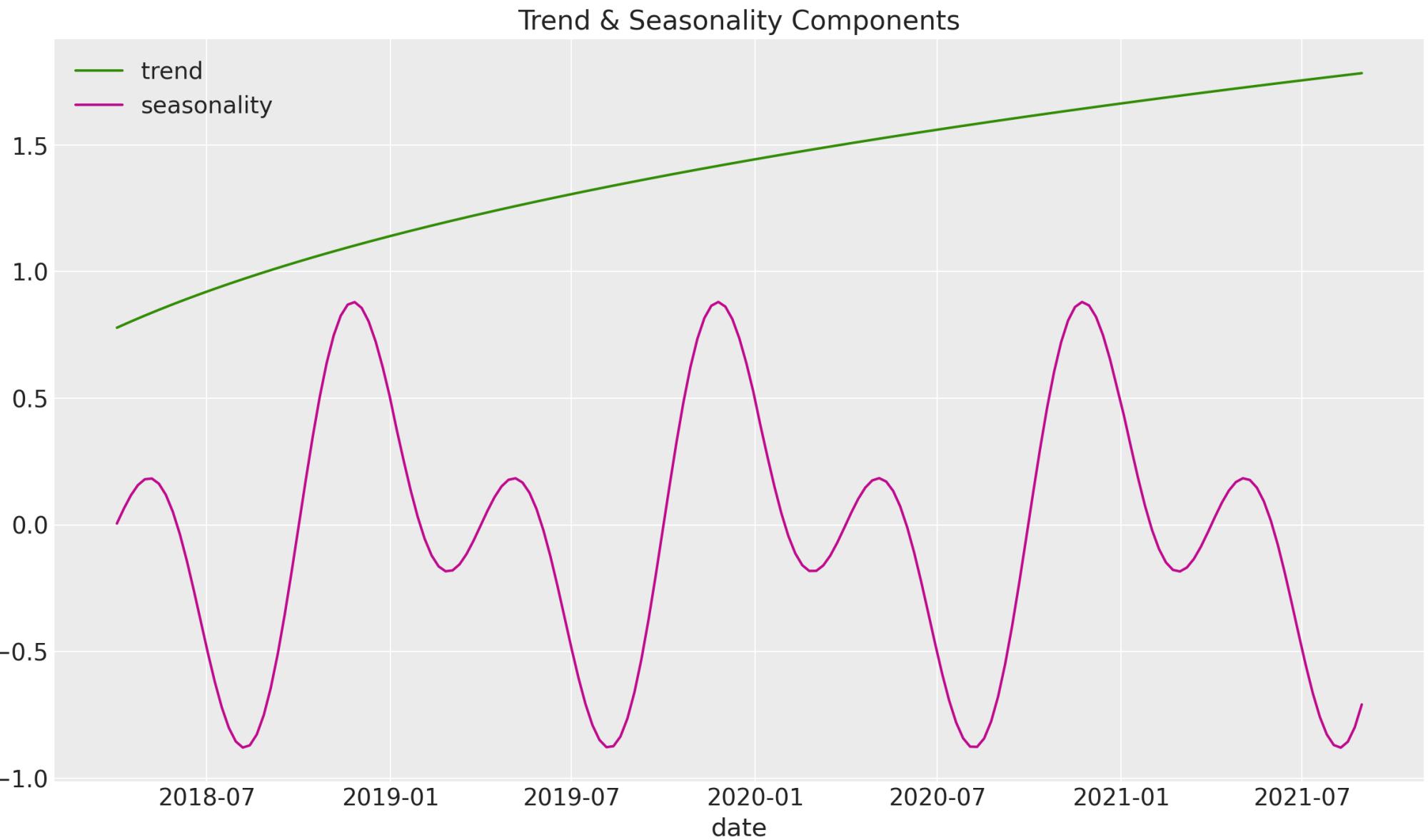
$$\text{saturation}(x_{m,t}; \lambda) = \frac{1 - \exp(-\lambda x_{m,t})}{1 + \exp(-\lambda x_{m,t})}$$



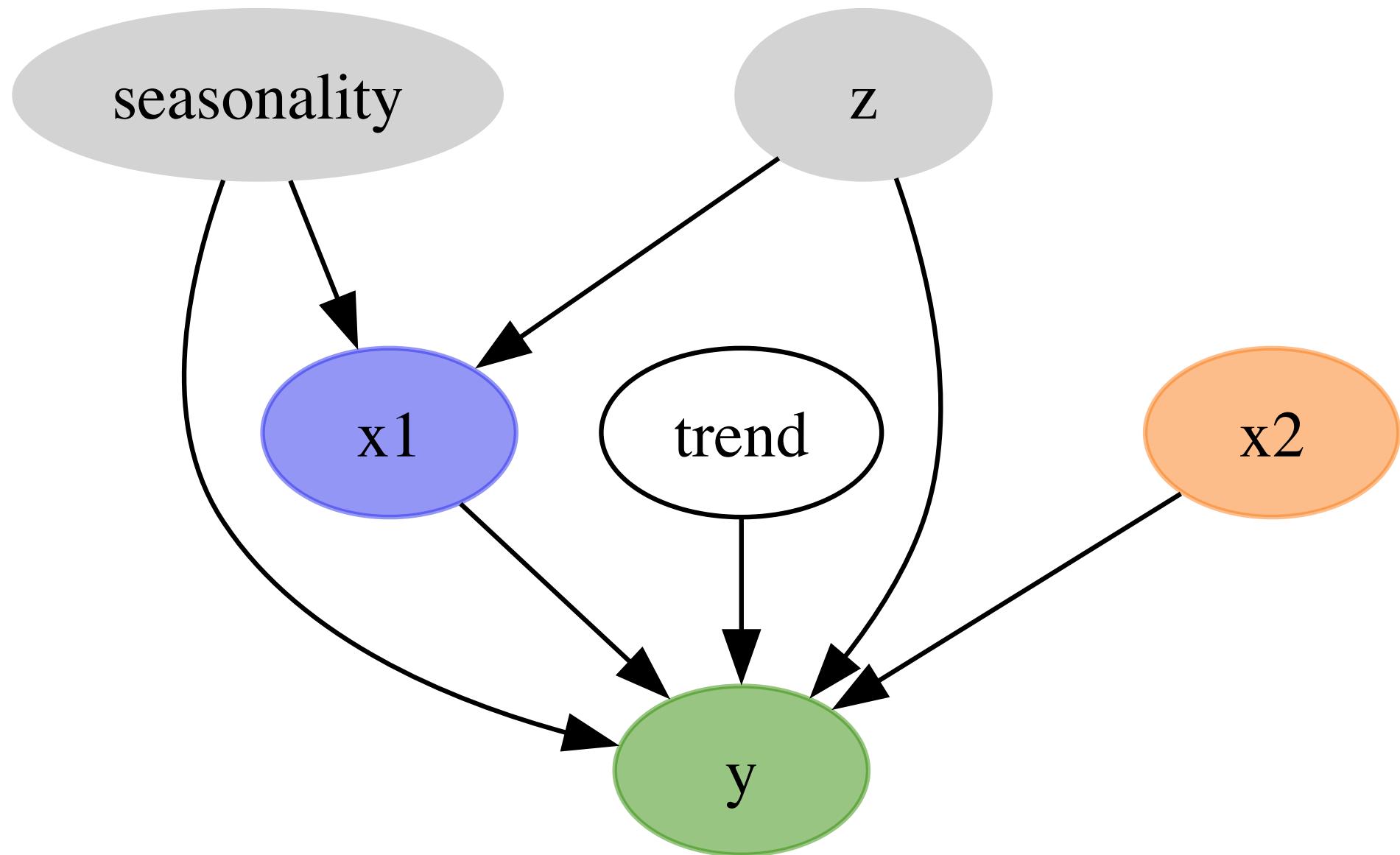
Media Transformations



Additional Effects



MMM as a Causal Model



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.



PyMC-Marketing



PyMC-Marketing

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

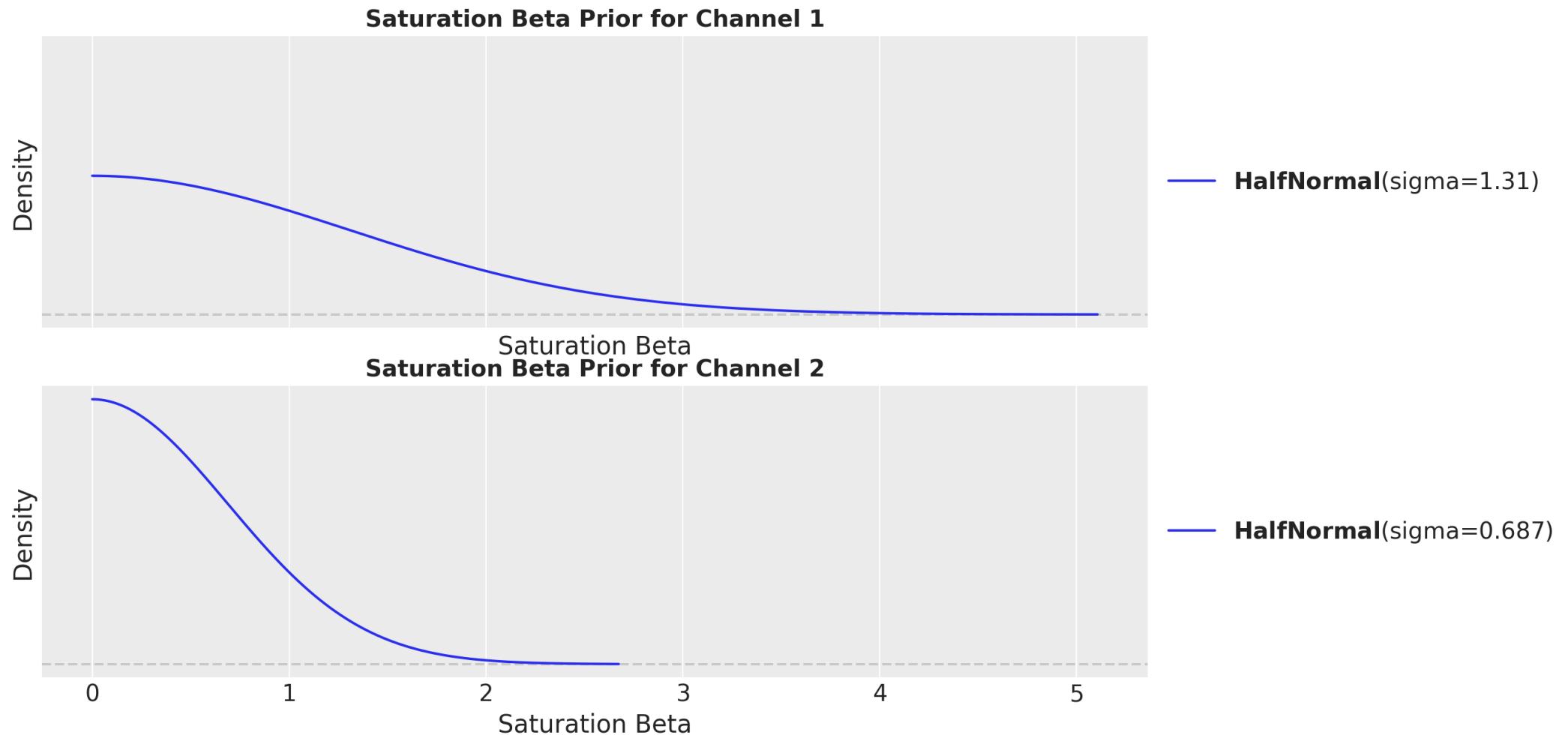


PyMC-Marketing API

```
1 from pymc_marketing.mmm import MMM, GeometricAdstock, LogisticSaturation
2 from pymc_marketing.prior import Prior
3
4 # Define priors
5 my_model_config = {
6     "intercept": Prior("Normal", mu=0.5, sigma=0.1),
7     ...,
8     "likelihood": Prior(
9         "TruncatedNormal", lower=0, sigma=Prior("Exponential", lam=1)
10    ),
11 }
12
13 # Define the model
14 mmm = MMM(
15     model_config=my_model_config,
16     date_column="date_week",
17     adstock=GeometricAdstock(l_max=8),
18     saturation=LogisticSaturation(),
19     channel_columns=channel_columns,
20     control_columns=control_columns,
21     time_varying_intercept=True,
```

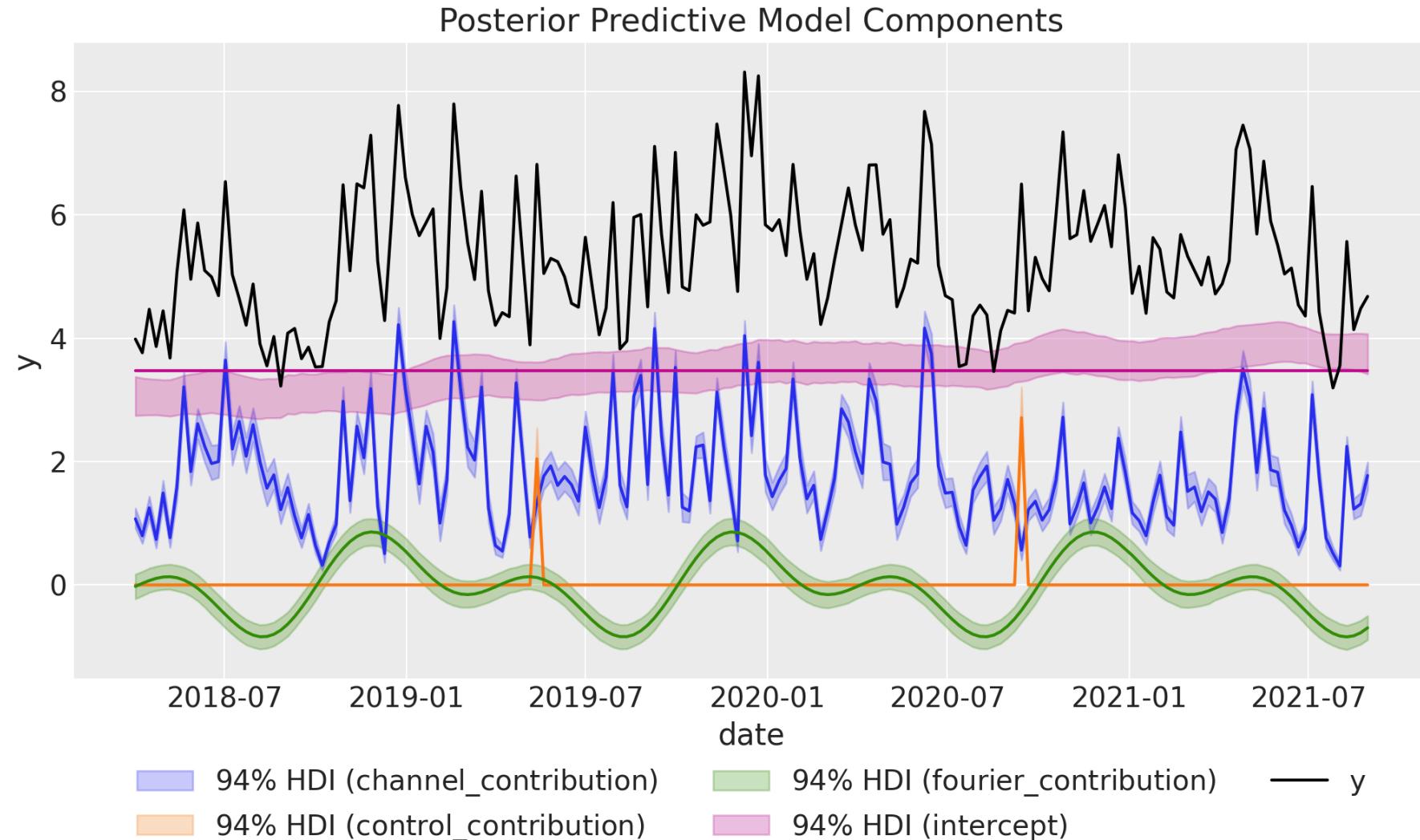


Prior Specification



Attribution Decomposition

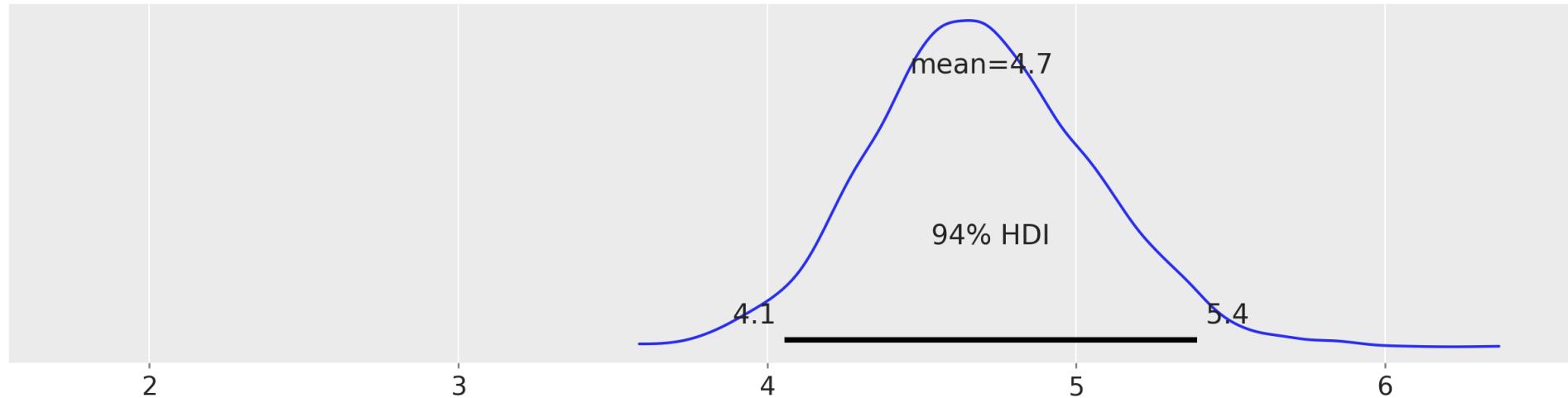
```
1 mmm.plot_components_contributions(original_scale=True);
```



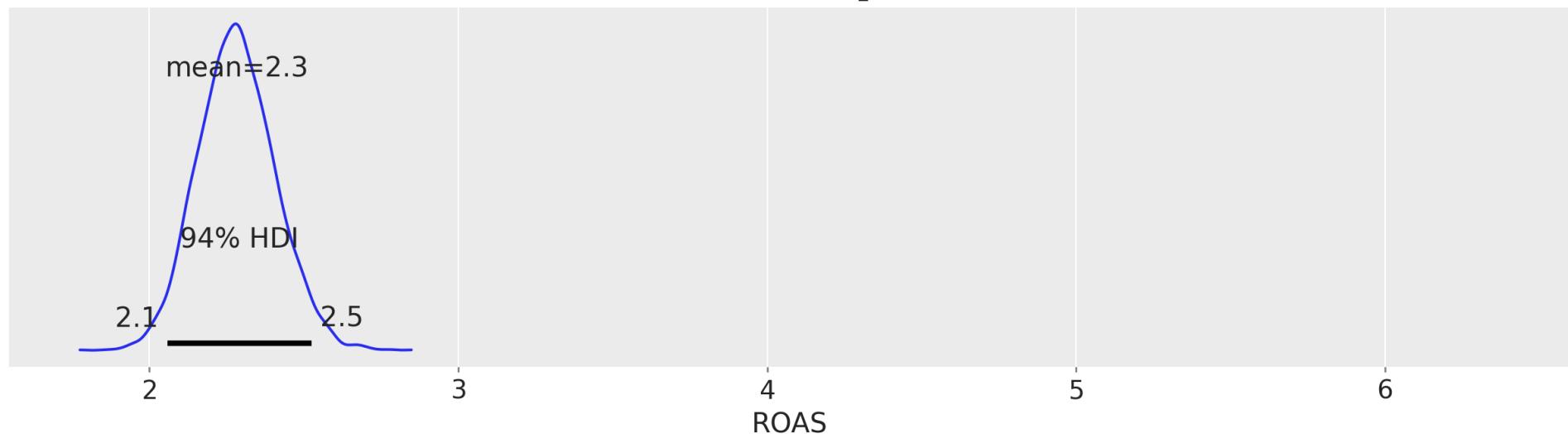
Return on Ad Spend (ROAS)

ROAS Posterior Distributions

Channel x_1

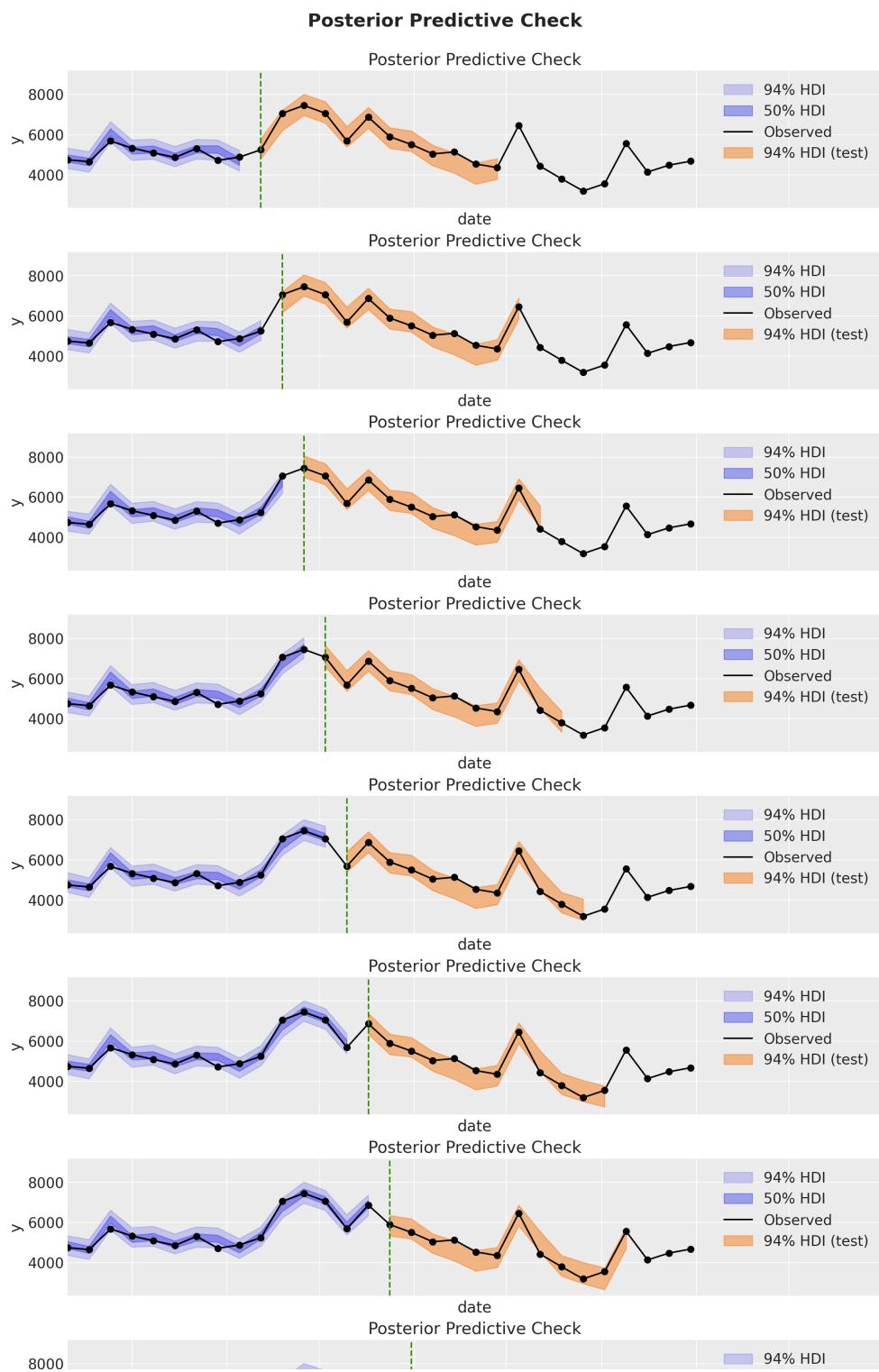


Channel x_2



Out-of-sample Forecasting



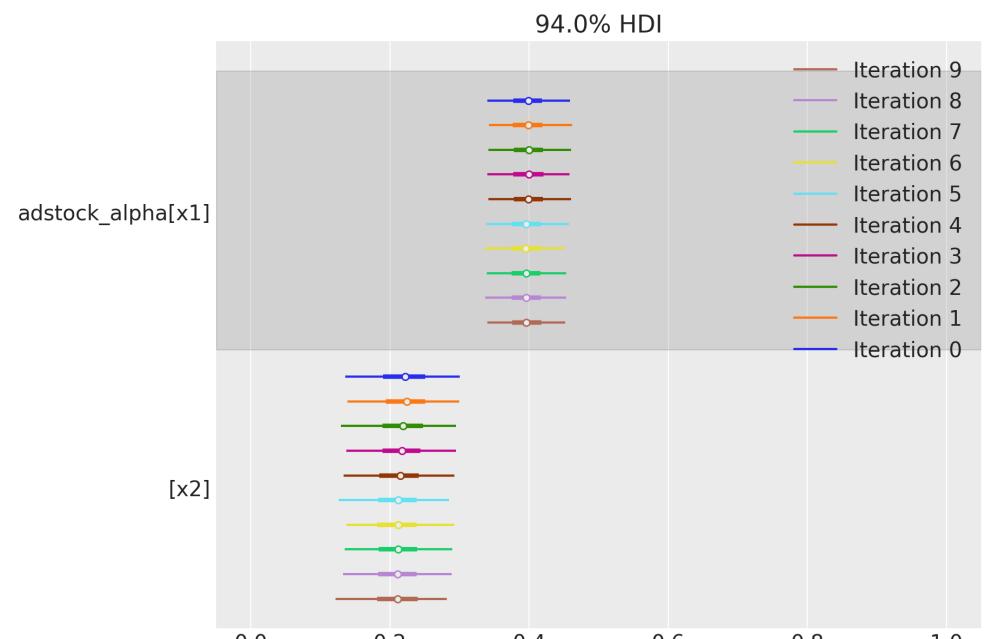


Model Evaluation Framework

Evaluate the model on the holdout set:

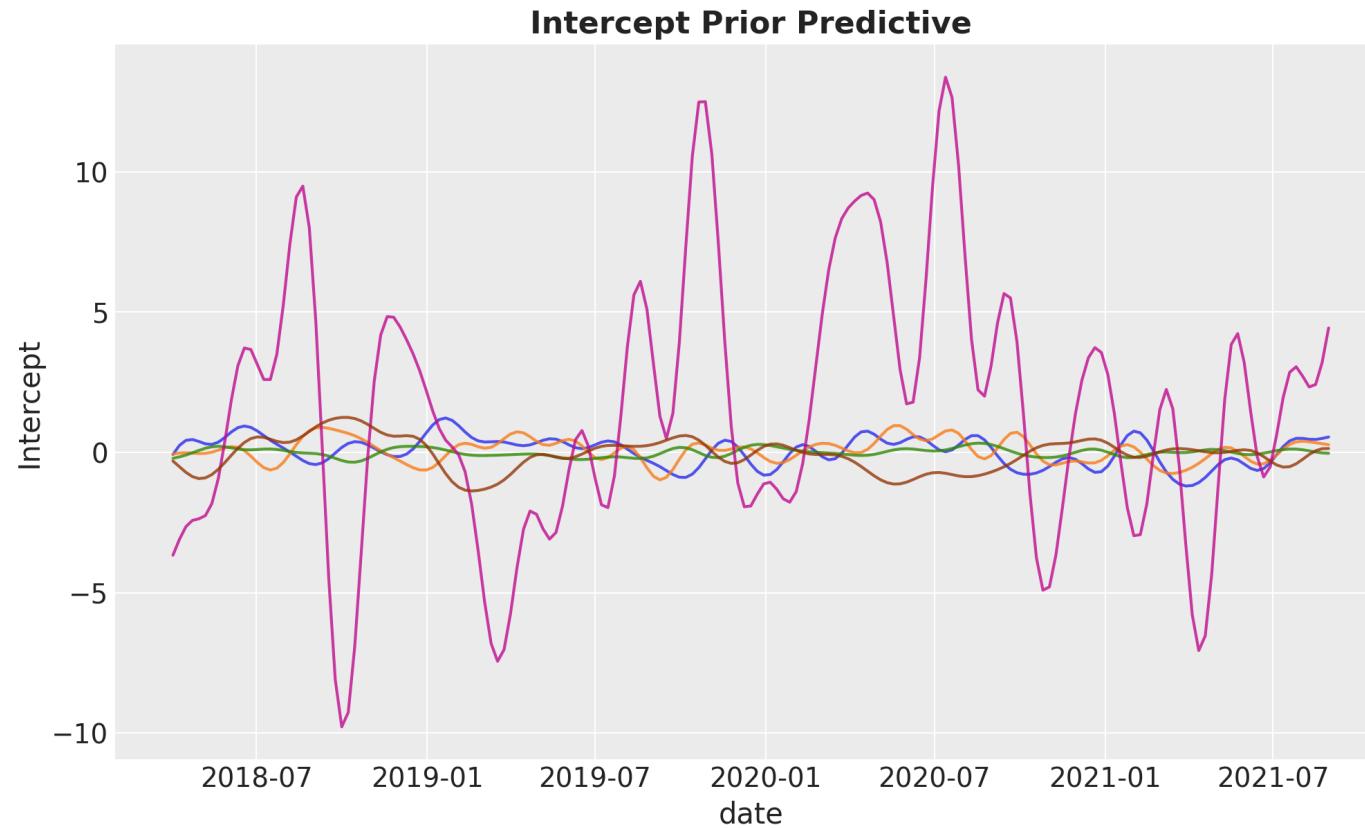
- Prediction accuracy (CRPS)
- Parameter Stability

Adstock Alpha

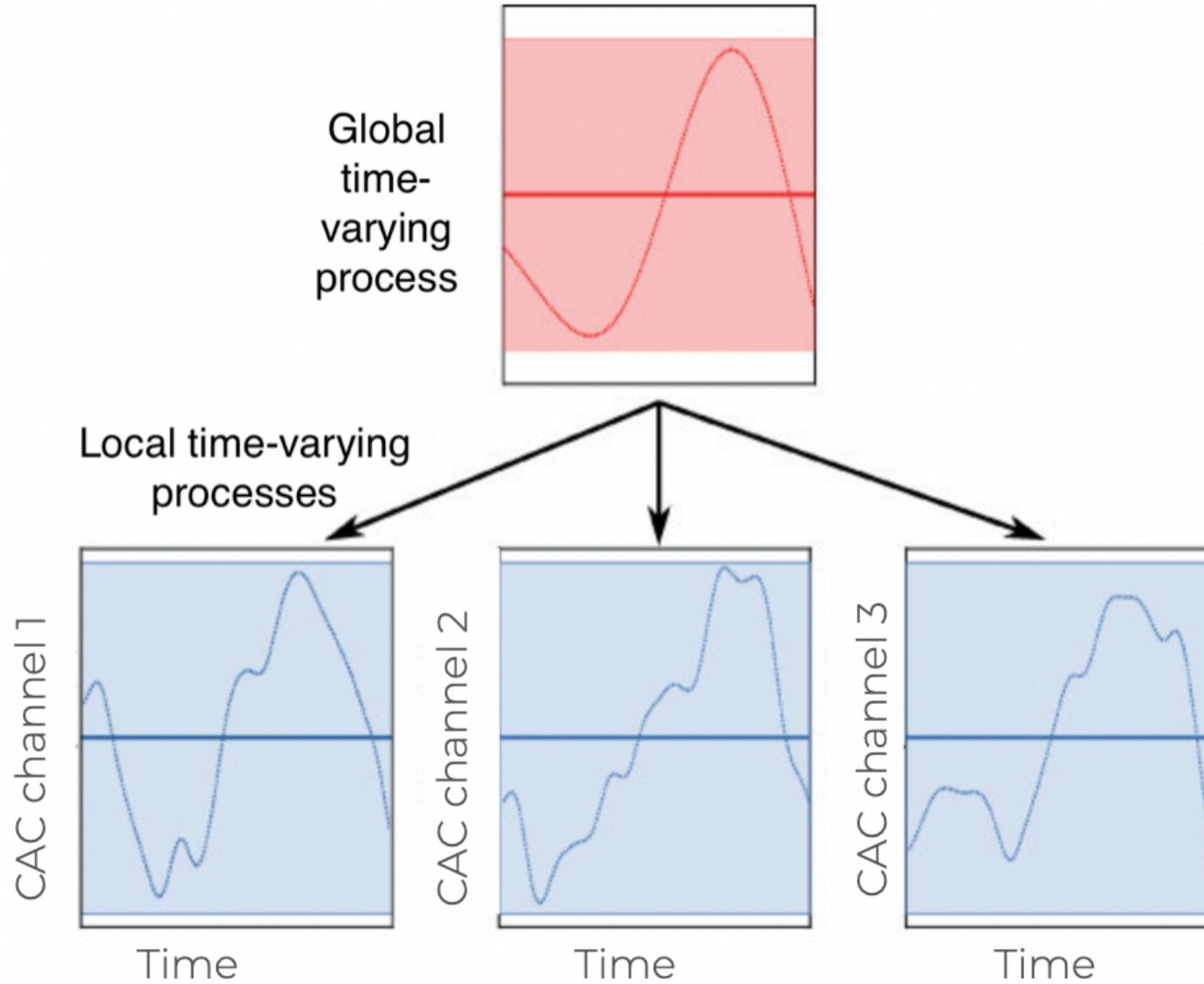


Time-varying Parameters

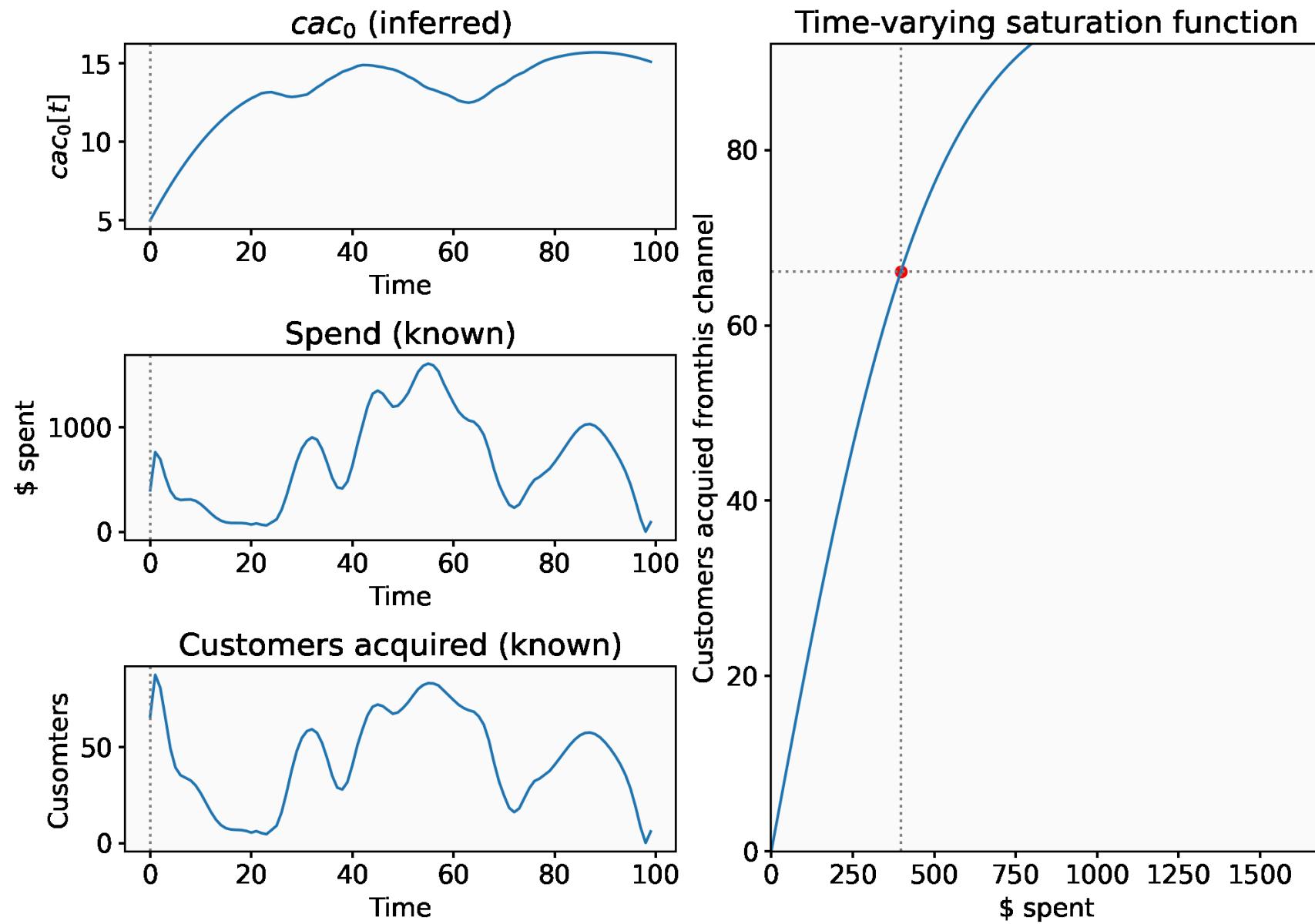
- Time-varying intercepts $b_t \sim \text{HSGP}(a, \ell, m)$
- Time-varying media effects $\beta_{m,t} \sim \text{HSGP}(a, \ell, m)$



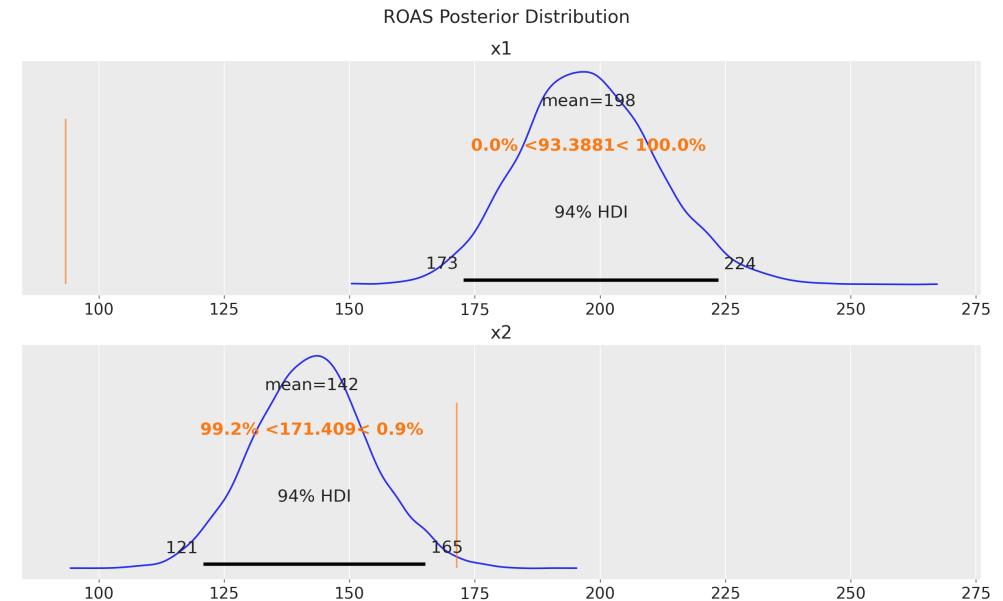
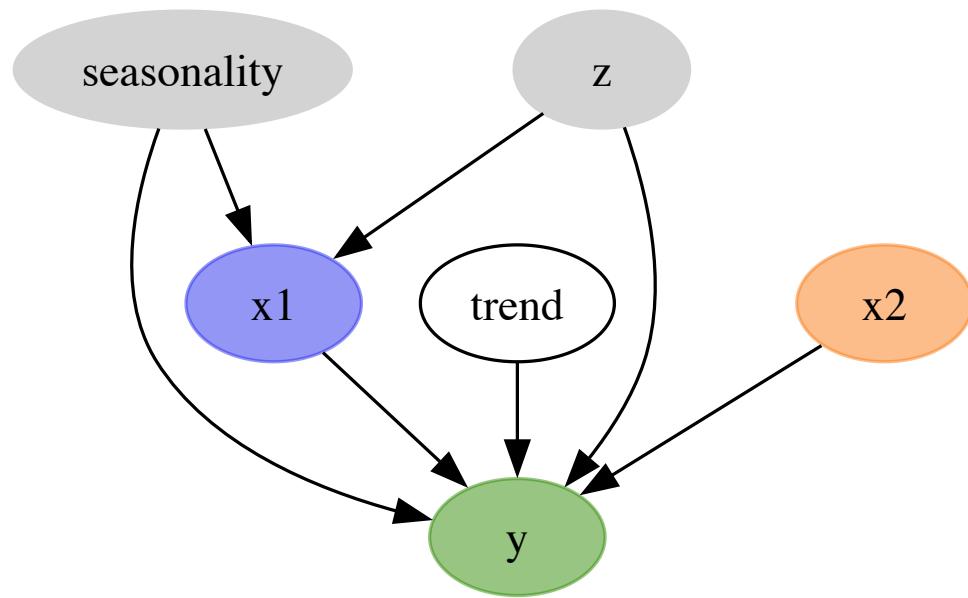
Hierarchical HSGP



Hierarchical Time-varying Parameters



Lift Test Calibration - Why?



! Important

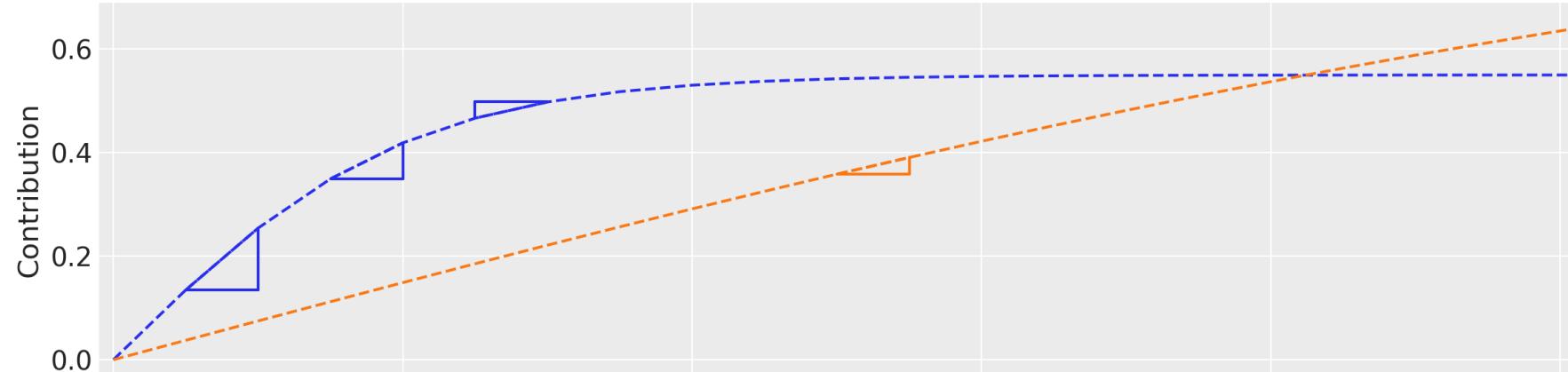
Unobserved confounders can bias the ROAS estimates and lead to wrong marketing strategies!



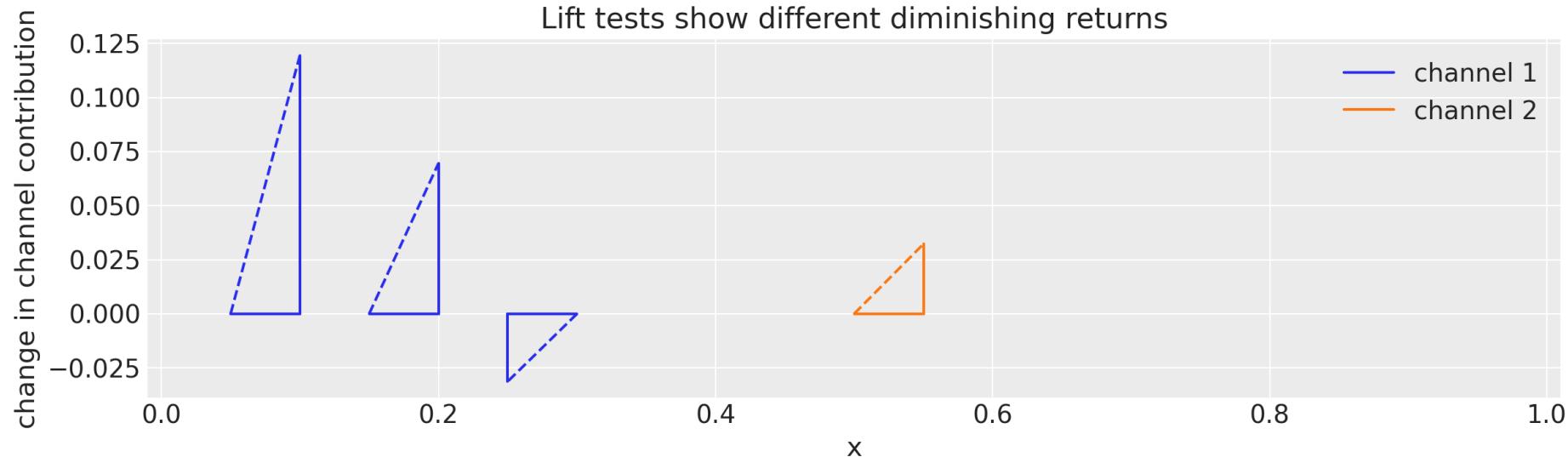
Lift Test Calibration

Saturation Curves

Lift tests results shown on top of actual curves

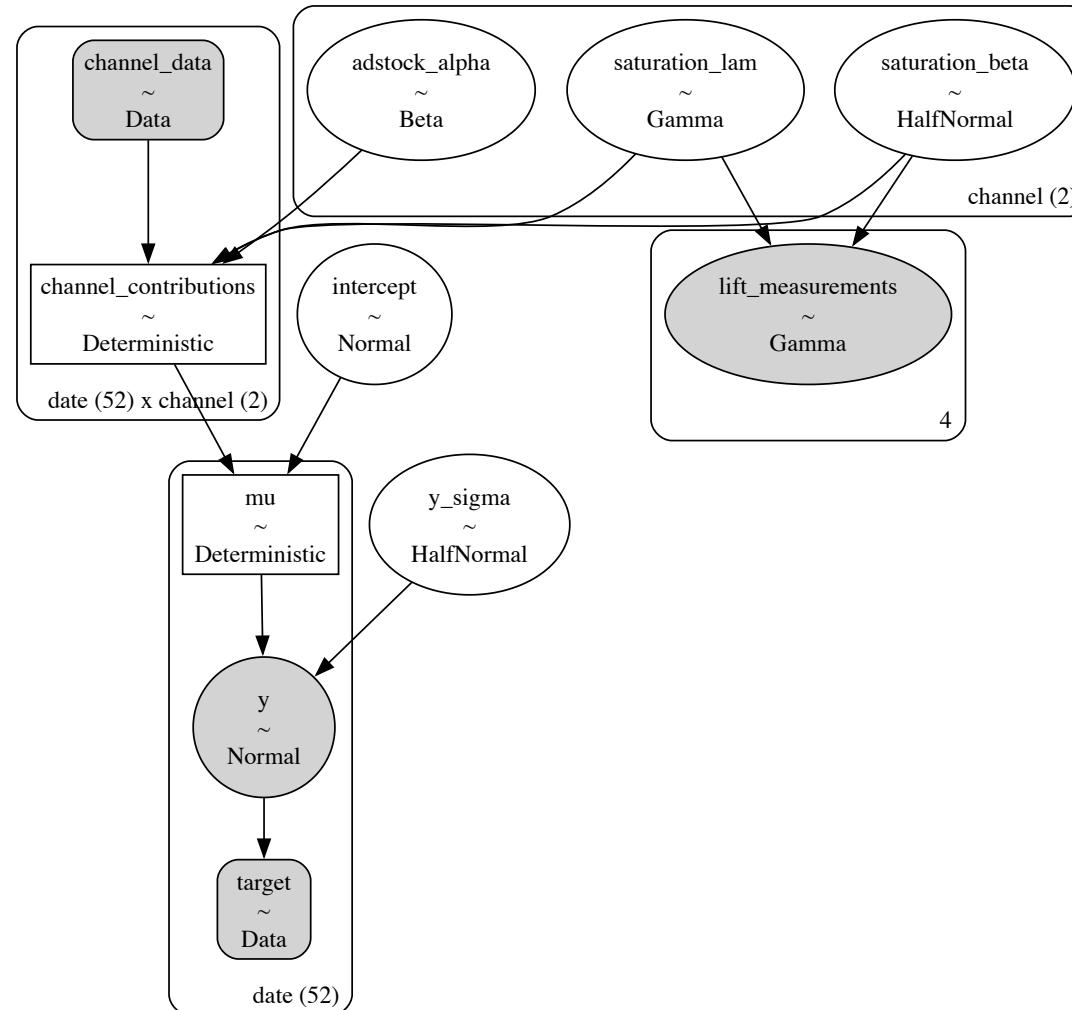


Lift tests show different diminishing returns



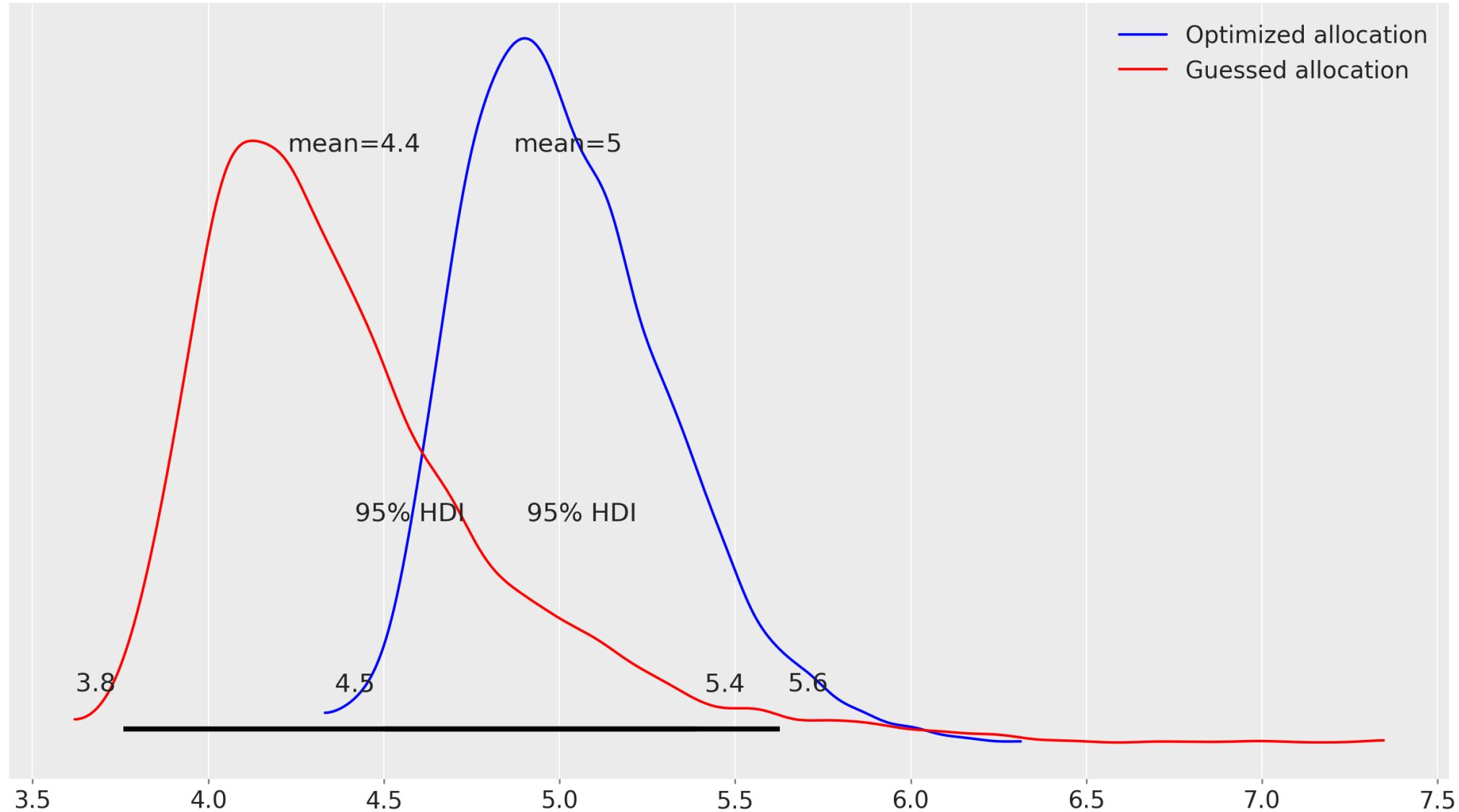
Lift Test Calibration

Additional Likelihood



Budget Optimization

Response Distribution at 95% HDI (highest density interval)



Thank You!

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