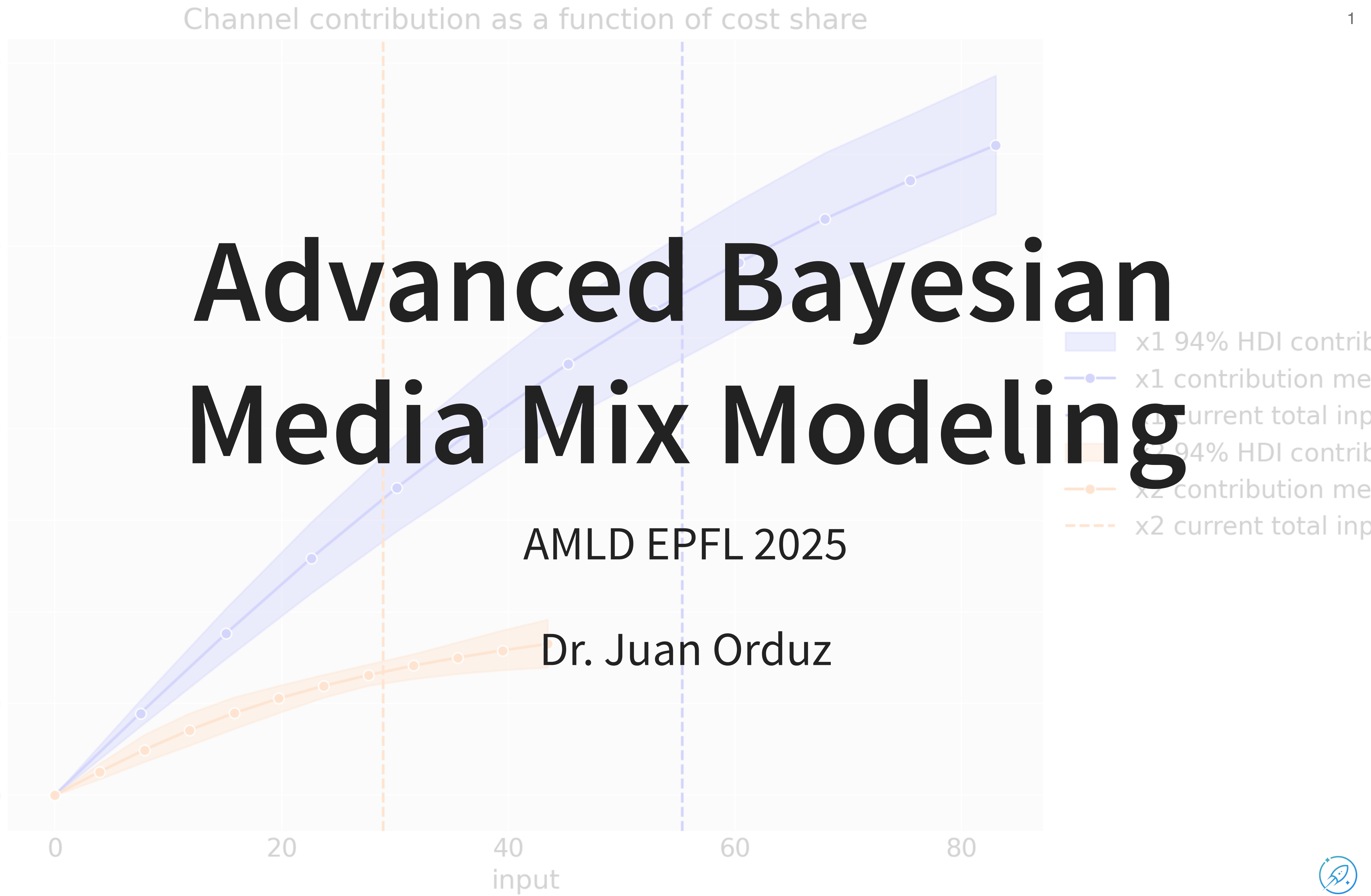

Advanced Bayesian Media Mix Modeling

AMLD EPFL 2025

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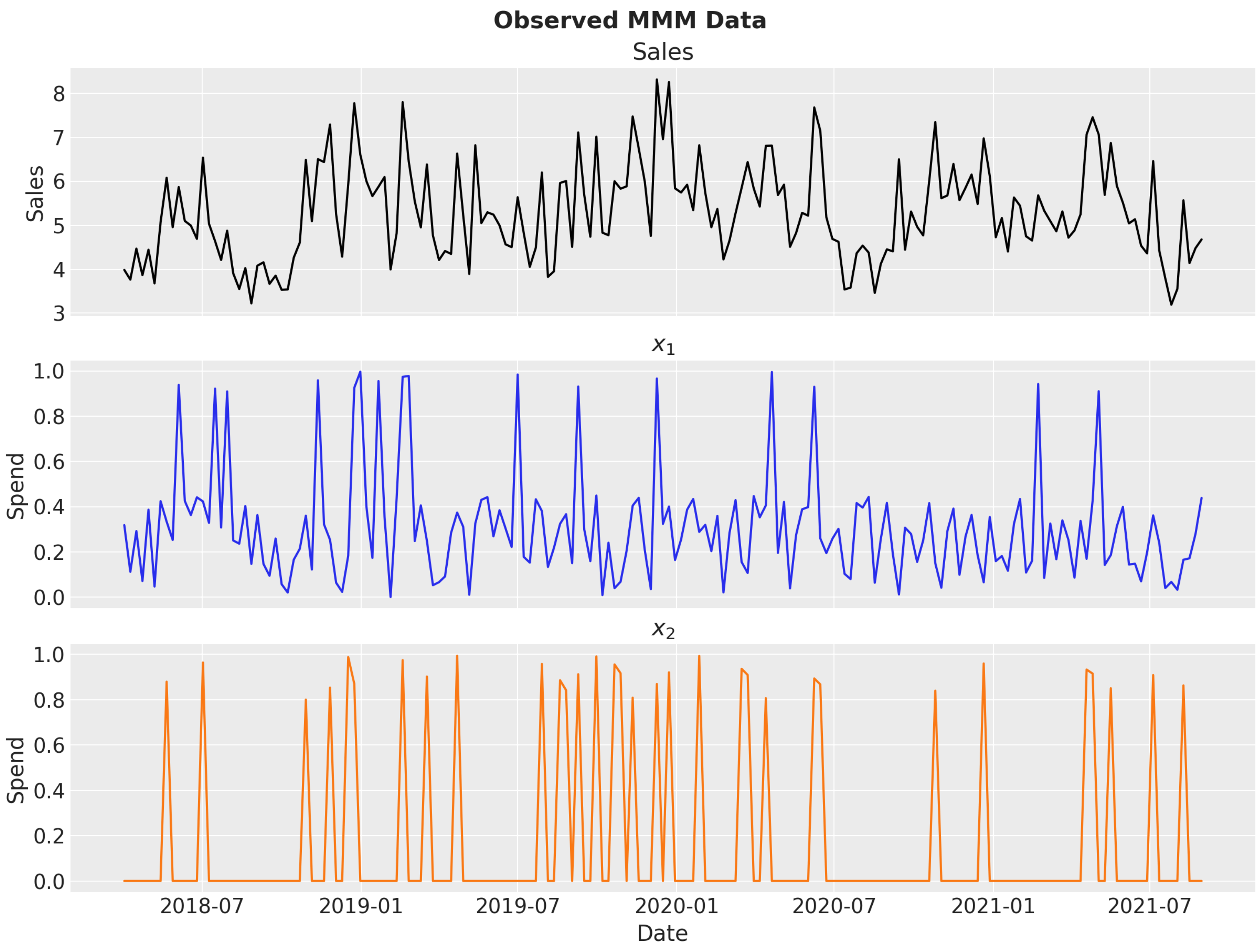
Outline

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
- PyMC-Marketing in production

What is Media Mix Modeling (MMM)?



MMM as a Regression Model

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

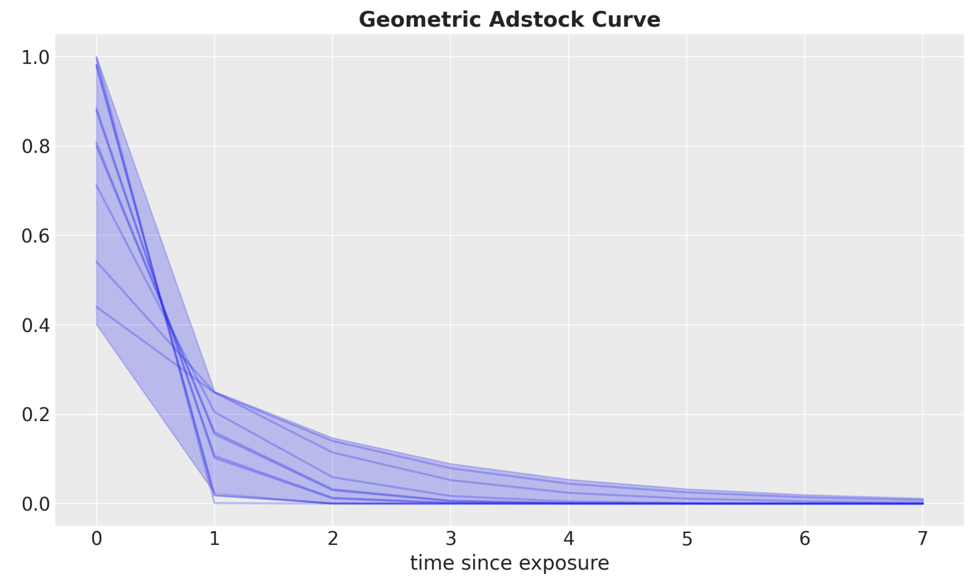
- y_t: Target variable at time t (e.g. sales, conversions, etc.)
- b_t: Baseline sales at time t
- $\beta_{m,t}$: Effect of media m on sales at time t
- $f(x_{m,t})$: Transformation of media m at time t
- γ_c: Effect of control variables $z_{c,t}$ on sales
- ε_t: Error term

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.

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

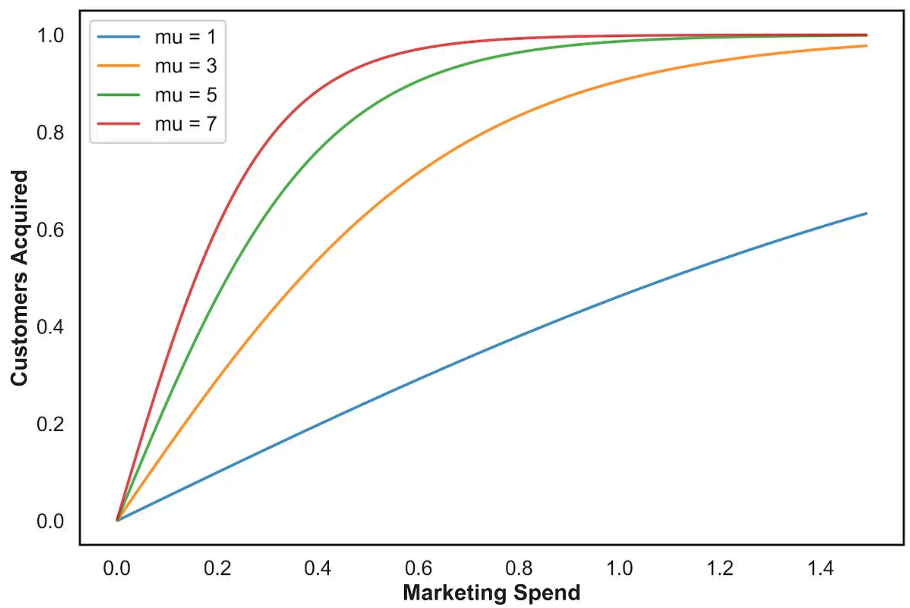
for $\alpha \in [0, 1]$ and T the number of periods.



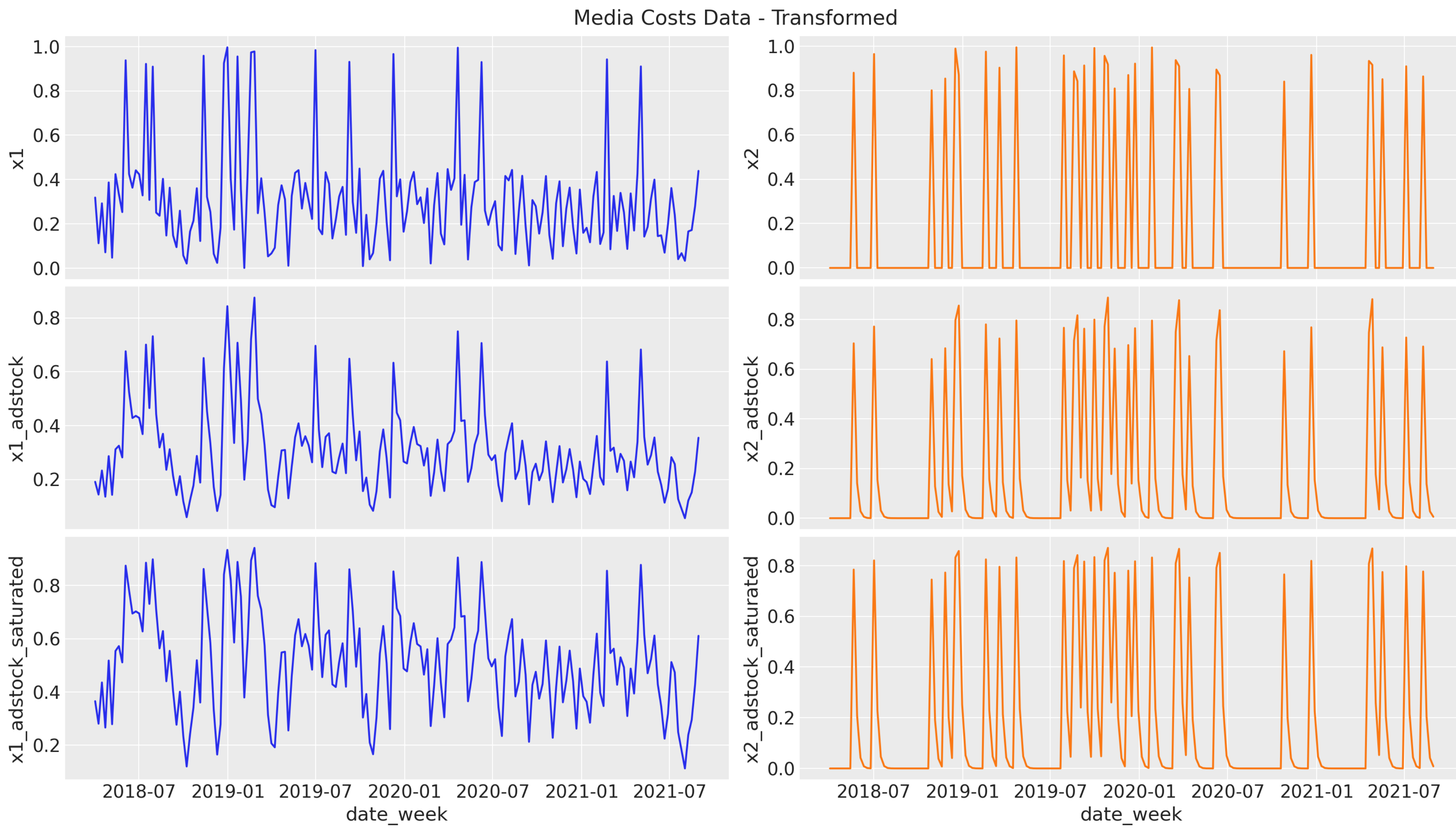
Saturation Effect

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

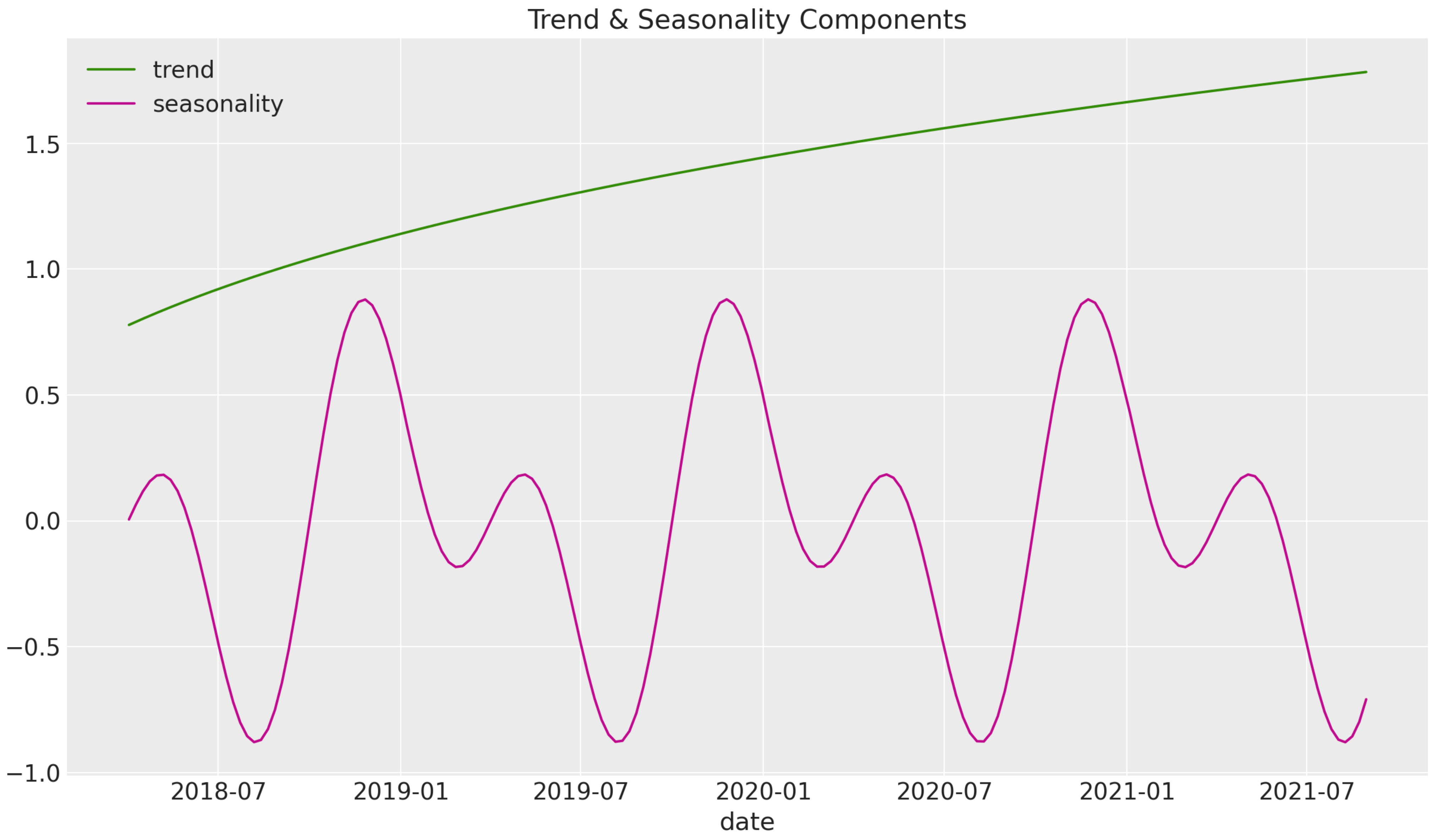
$$\text{saturation}(x_{m,t};\lambda) = \frac{1-\exp(-\lambda x_{m,t})}{1+\exp(-\lambda x_{m,t})}$$



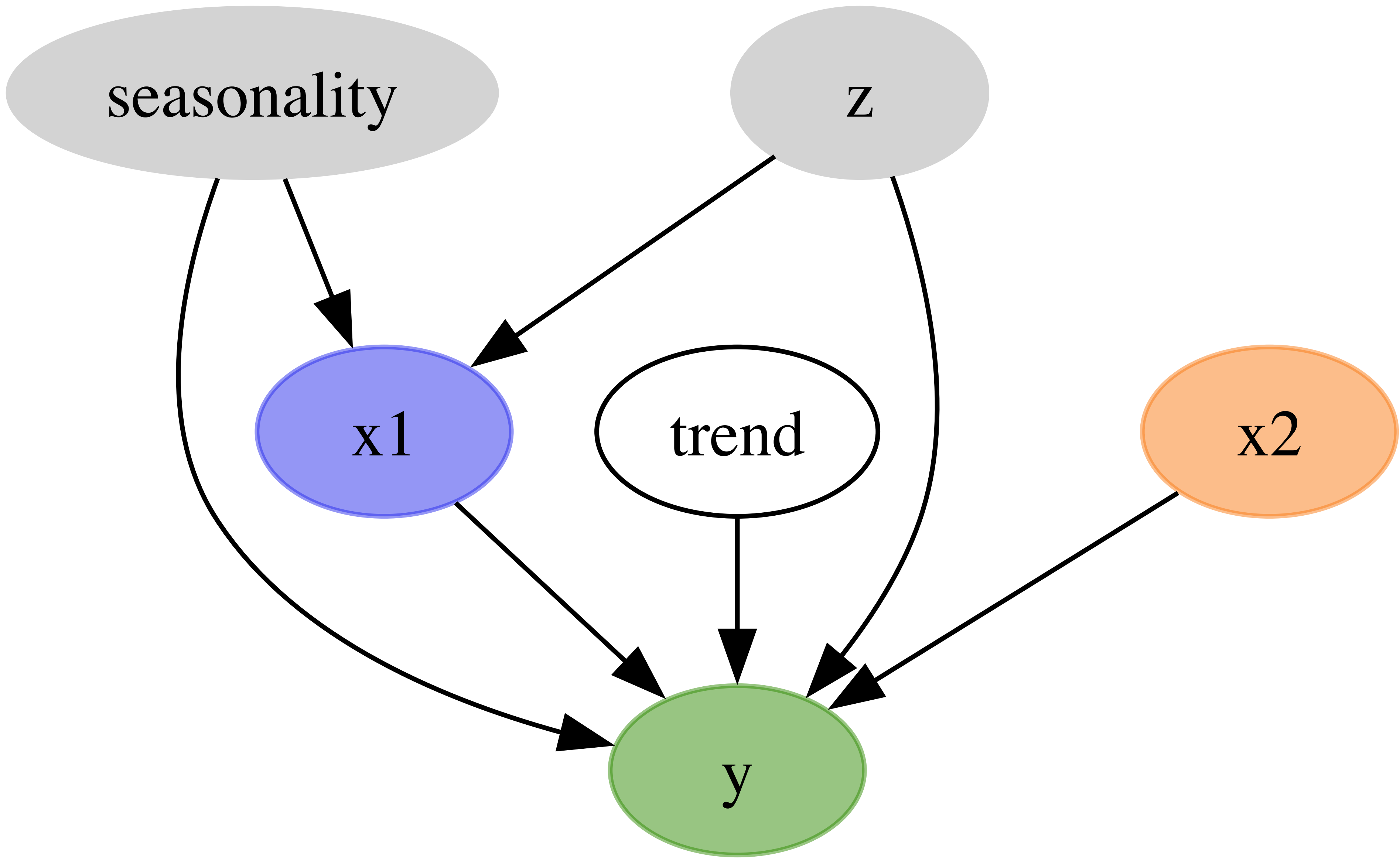
Media Transformations



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.

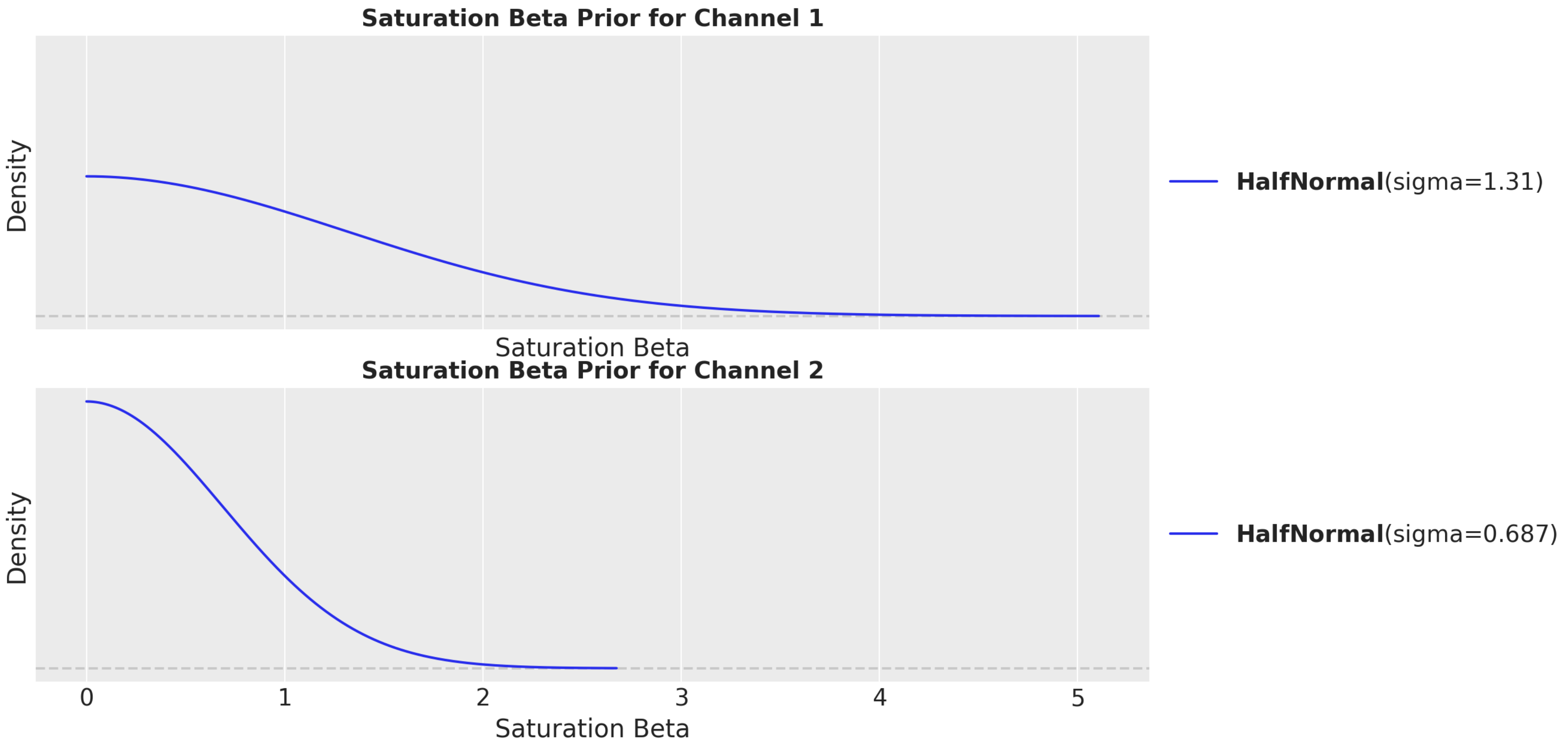
PyMC-Marketing

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

PyMC-Marketing API

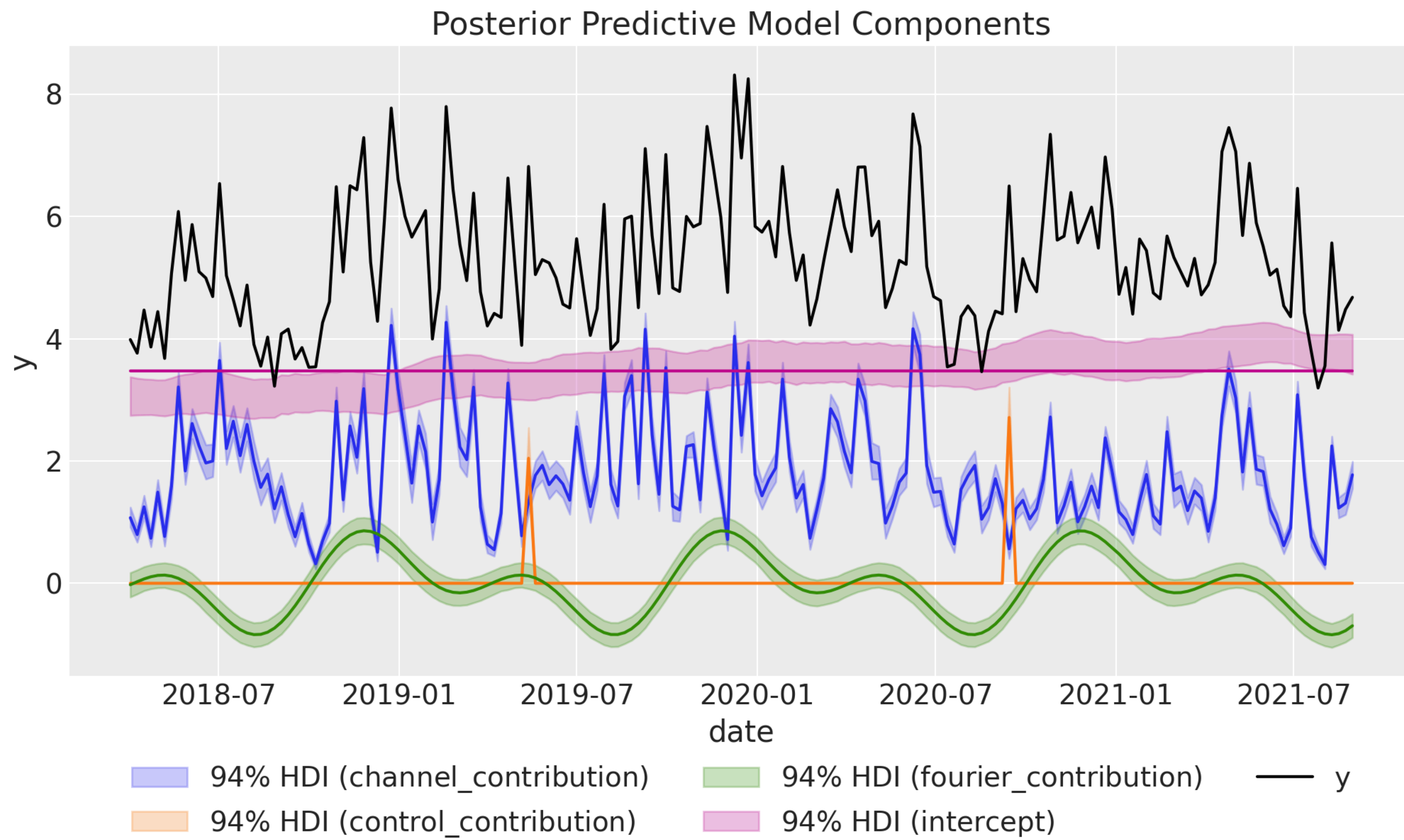
```python
from pymc_marketing.mmm import MMM, GeometricAdstock, LogisticSaturation
from pymc_marketing.prior import Prior

# Define priors
my_model_config = {
    "intercept": Prior("Normal", mu=0.5, sigma=0.1),
    ...,
    "likelihood": Prior(
        "TruncatedNormal", lower=0, sigma=Prior("Exponential", lam=1)
    ),
}

# Define the model
mmm = MMM(
    model_config=my_model_config,
    date_column="date_week",
    adstock=GeometricAdstock(l_max=8),
    saturation=LogisticSaturation(),
    channel_columns=channel_columns,
    control_columns=control_columns,
    time_varying_intercept=True,
```

Prior Specification

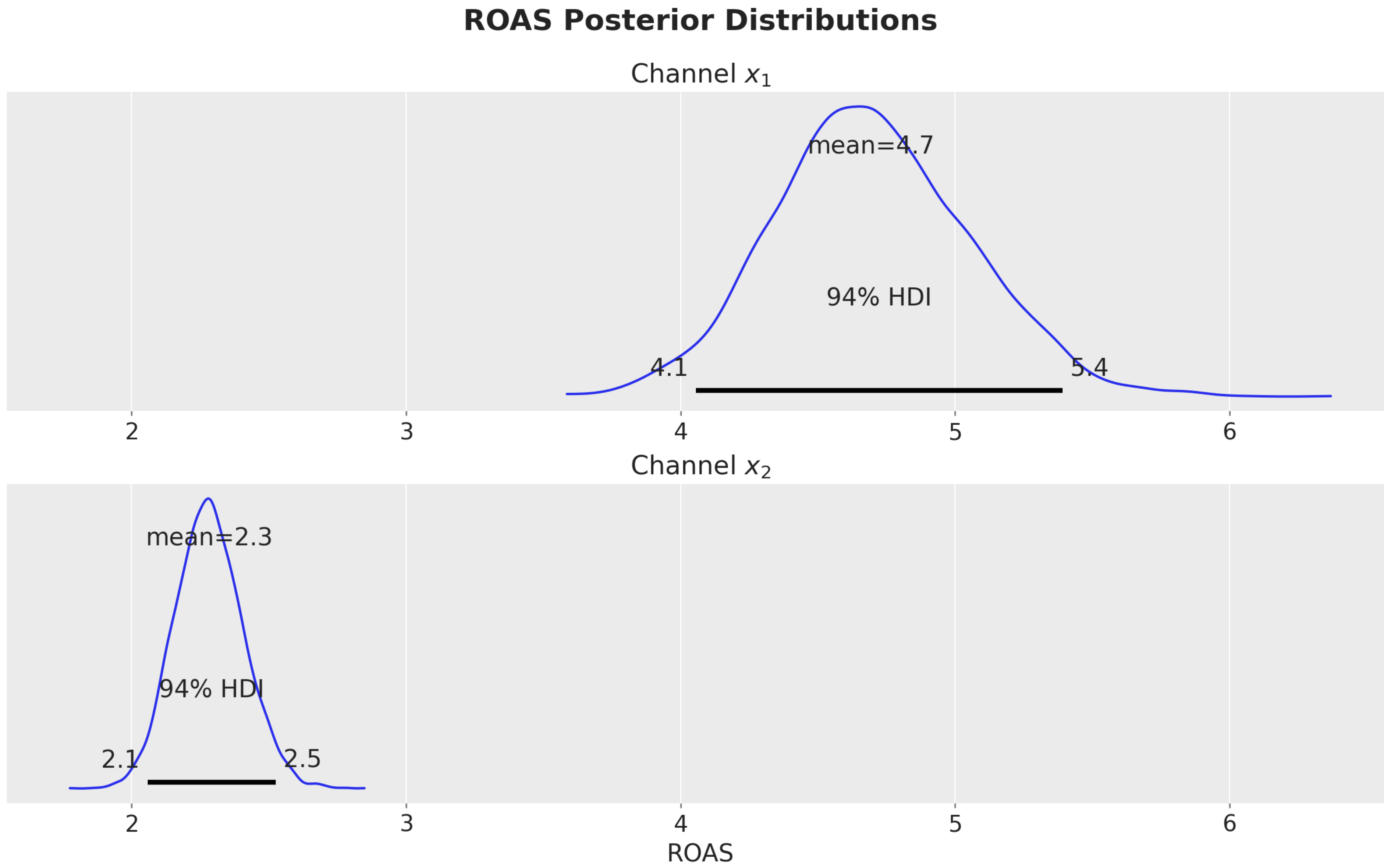


Attribution Decomposition

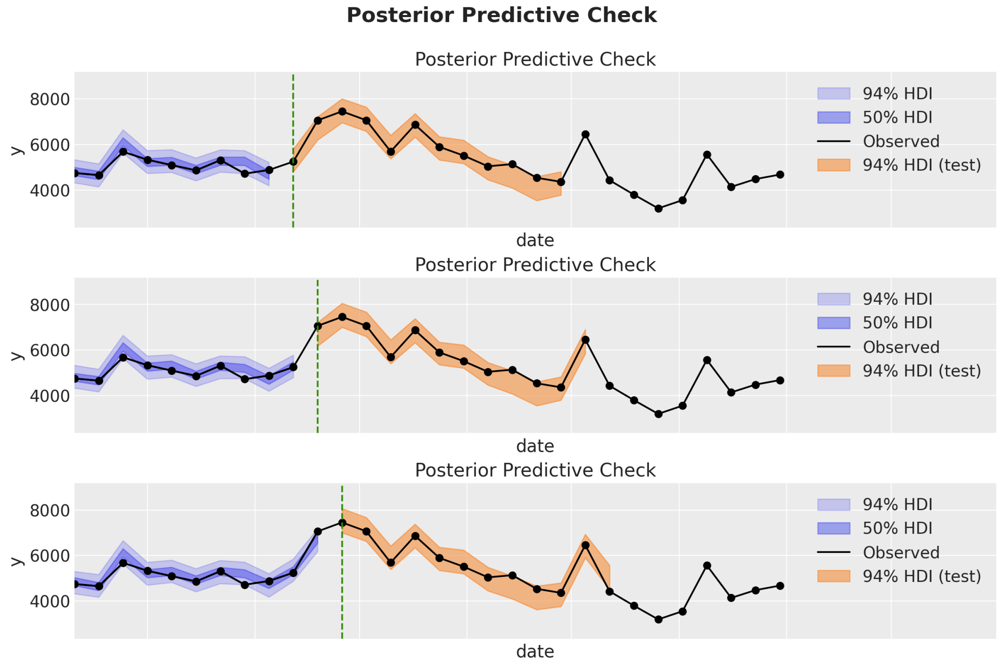
```
mmm.plot_components_contributions(original_scale=True);
```



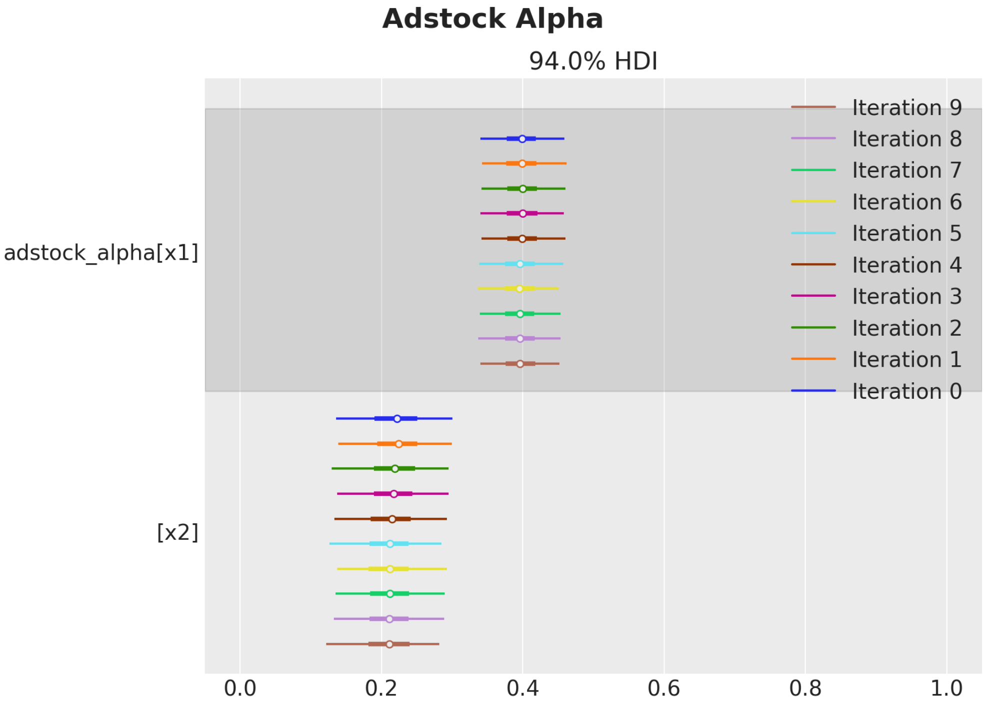
Return on Ad Spend (ROAS)



Out-of-sample Forecasting



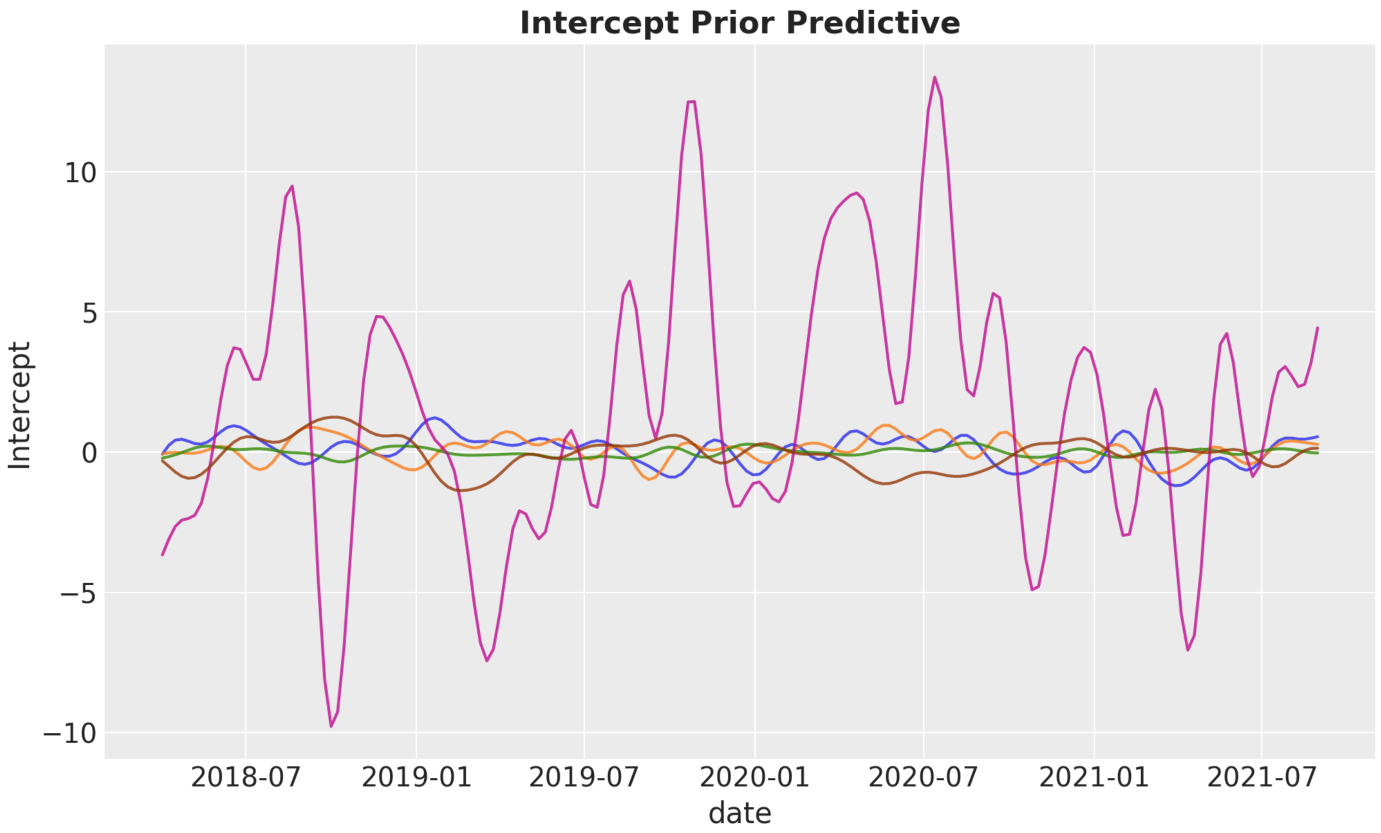
Prediction accuracy (CRPS)



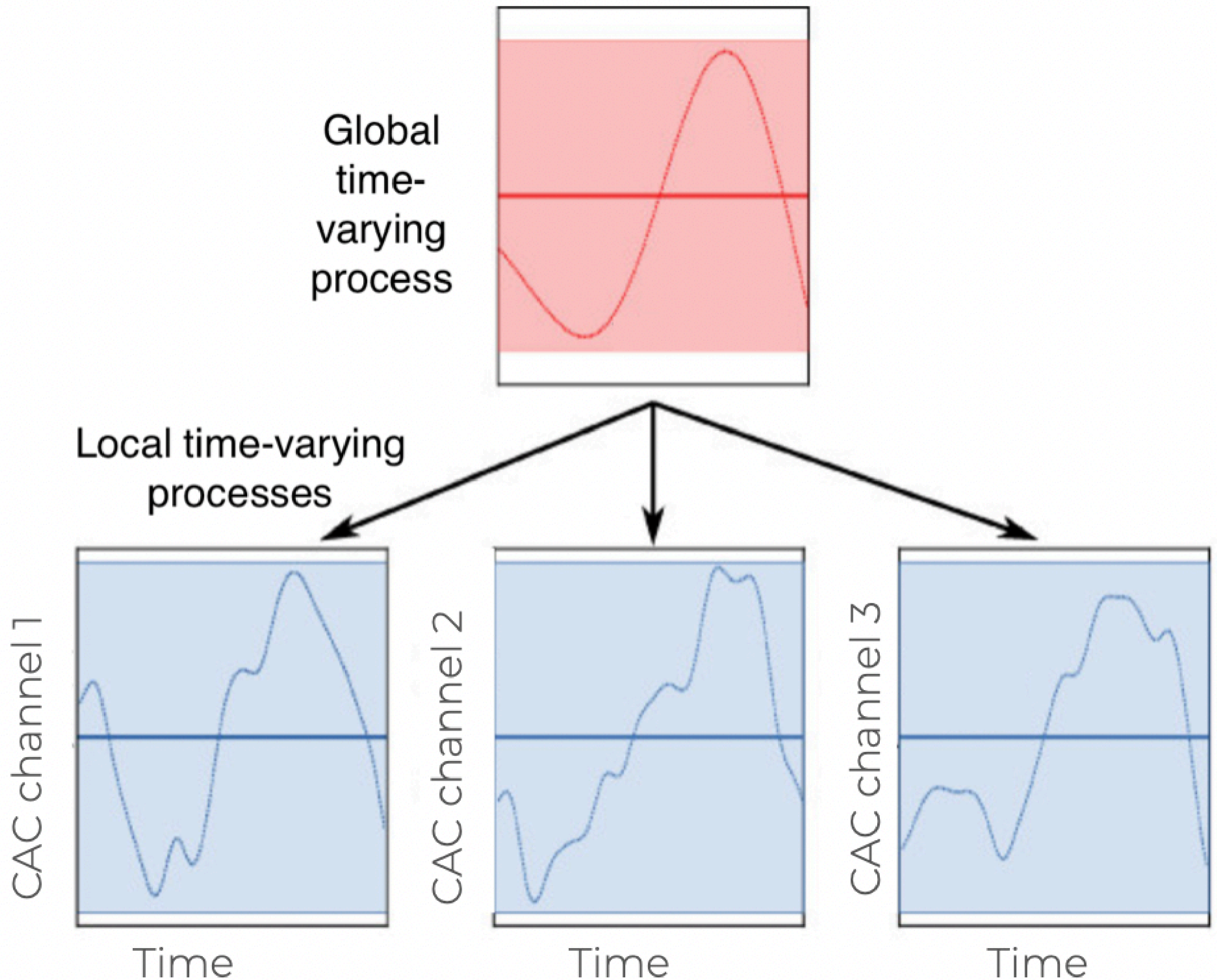
Parameter Stability

Time-varying Parameters

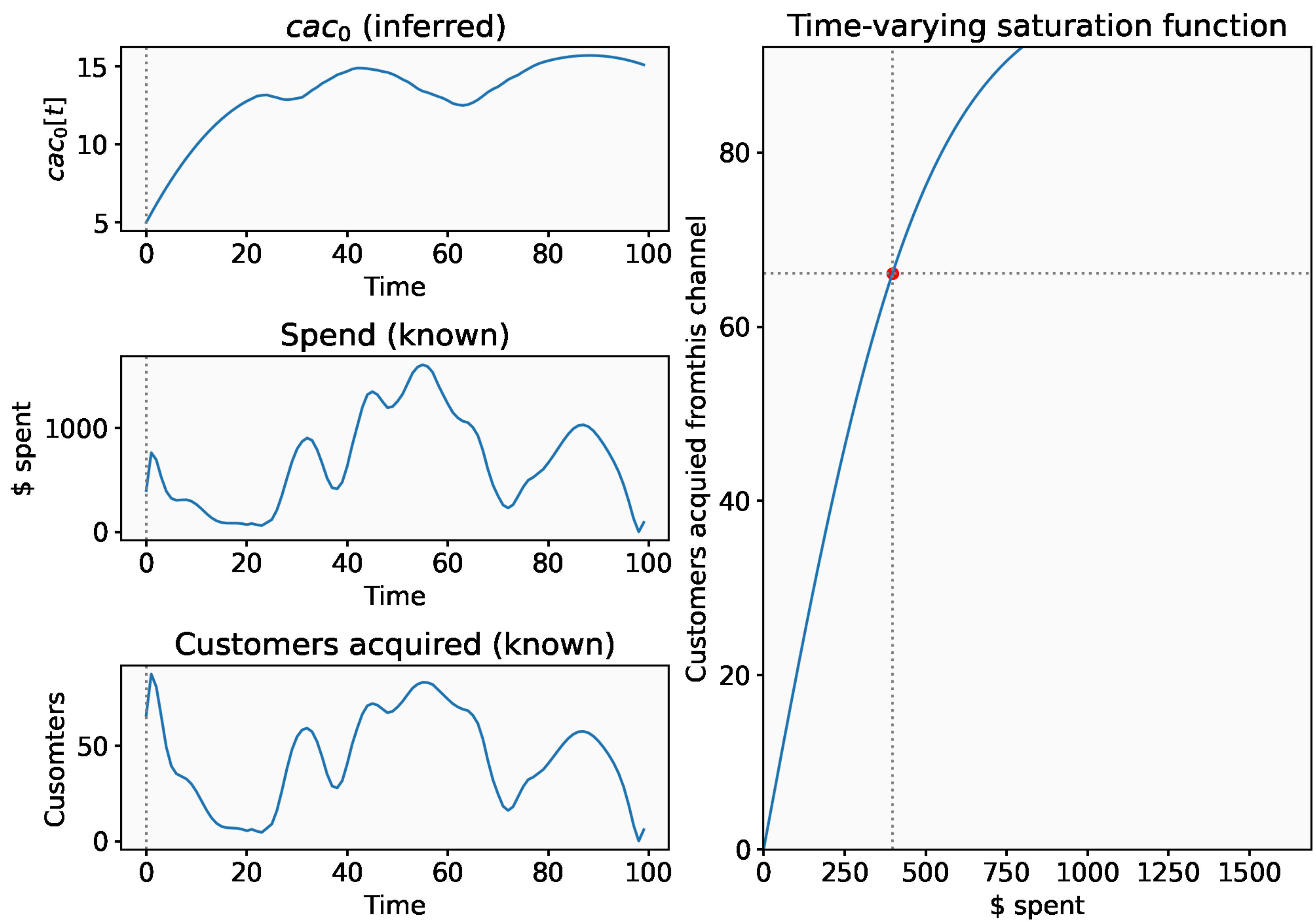
- Time-varying intercepts $b_t \sim \mathrm{HSGP}(a, \ell, m)$
- Time-varying media effects $\beta_{m,t} \sim \mathrm{HSGP}(a, \ell, m)$



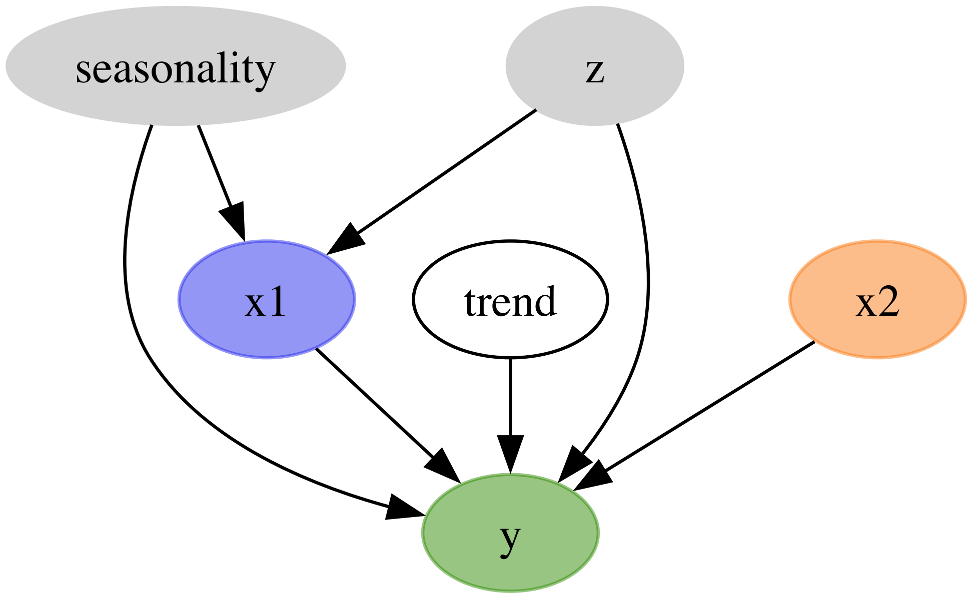
Hierarchical HSGP

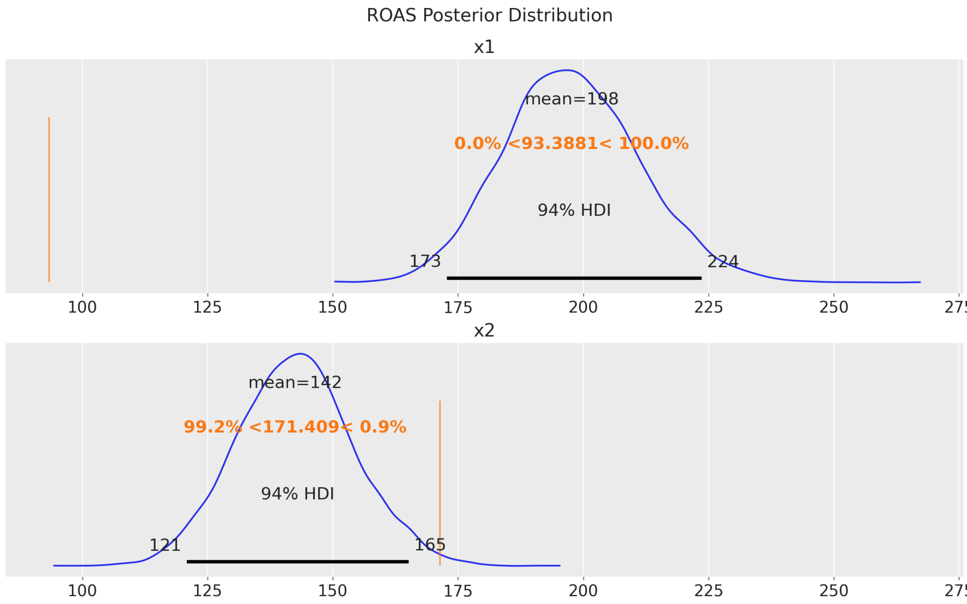


Hierarchical Time-varying Parameters



Lift Test Calibration - Why?





Important

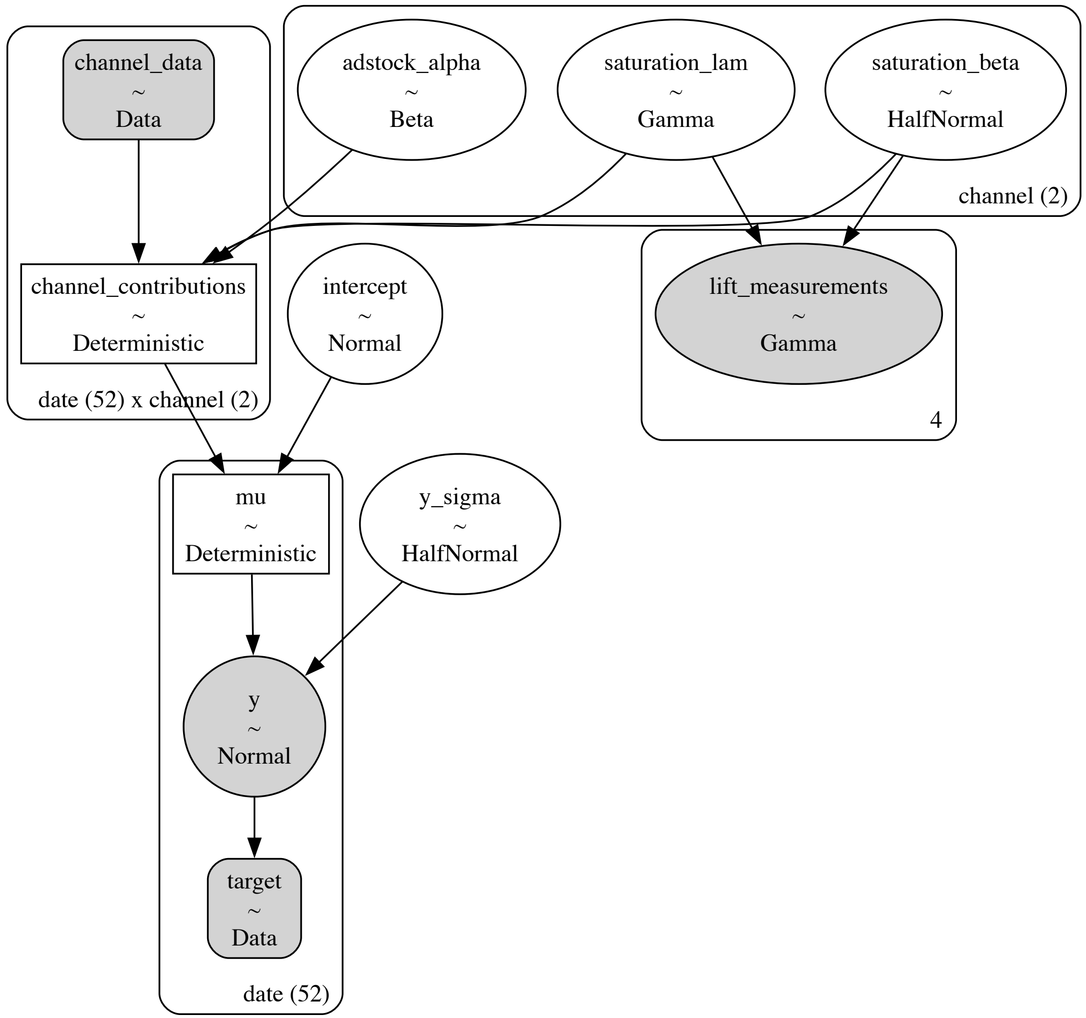
Unobserved confounders can bias the ROAS estimates and lead to wrong marketing strategies!

Lift Test Calibration

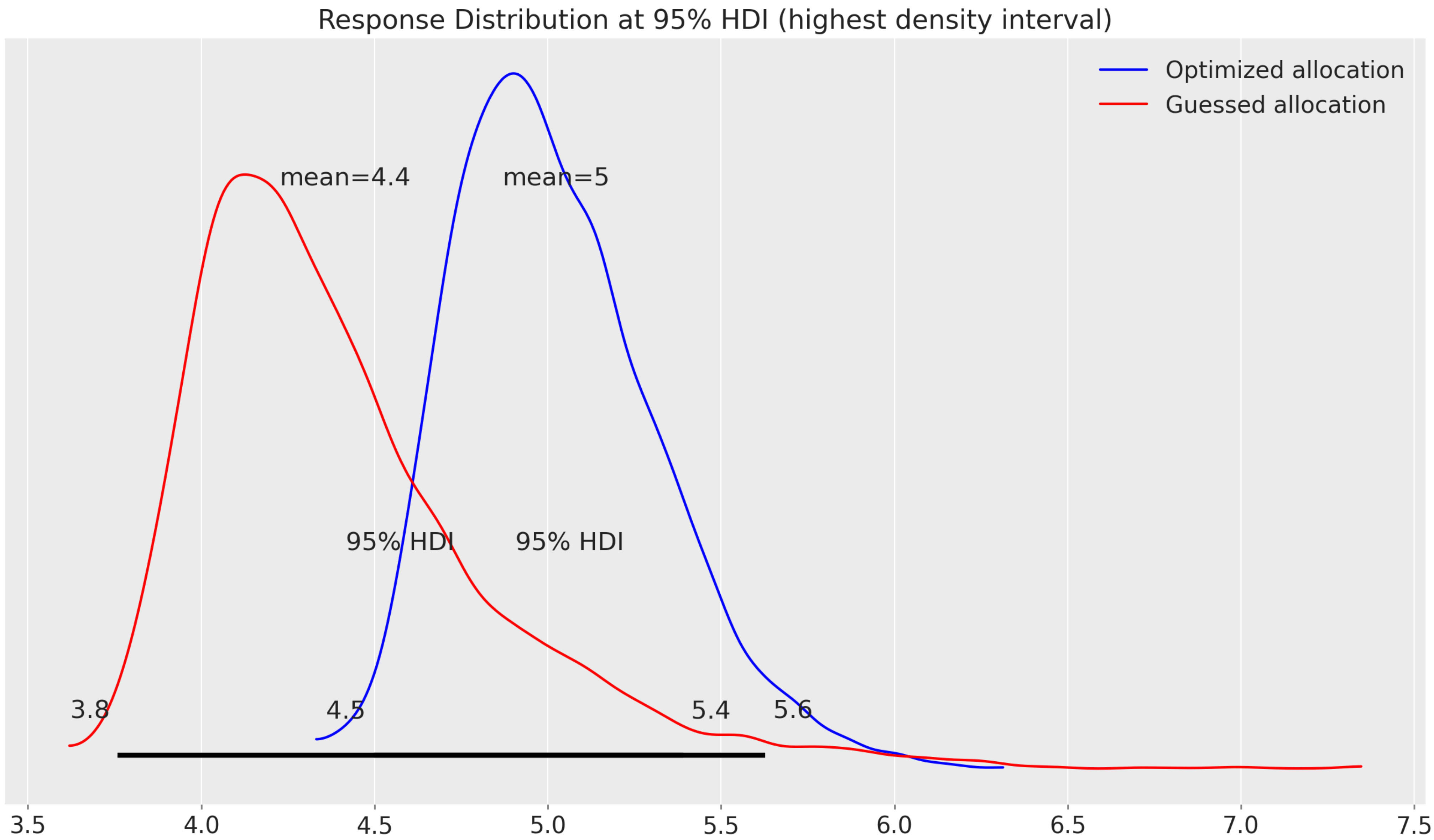
Saturation Curves

Lift Test Calibration

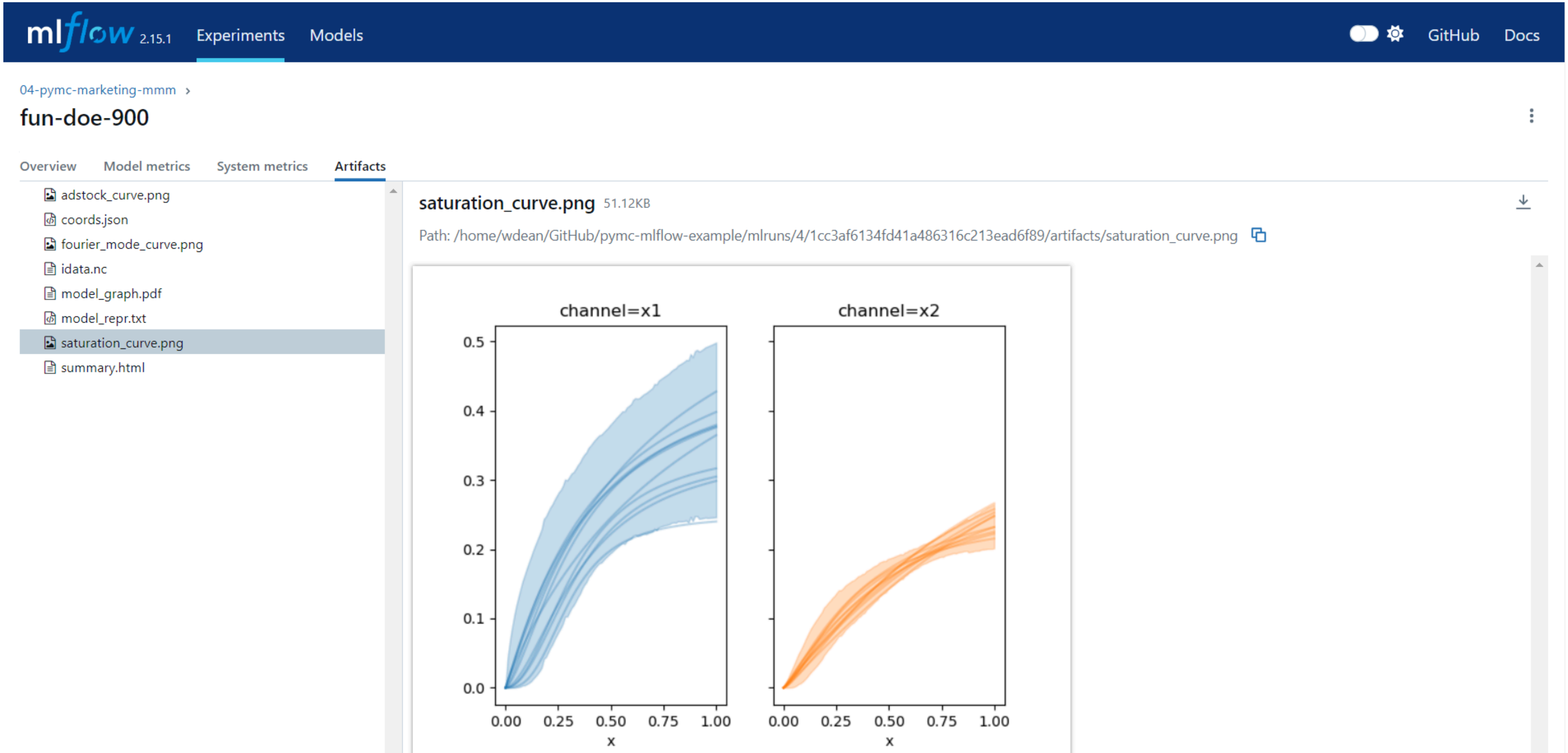
Additional Likelihood



Budget Optimization



PyMC-Marketing in Production



Thank You!

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