Your MMM Is Broken:
Identification of Nonlinear and Dynamic Effects in Marketing Mix Models

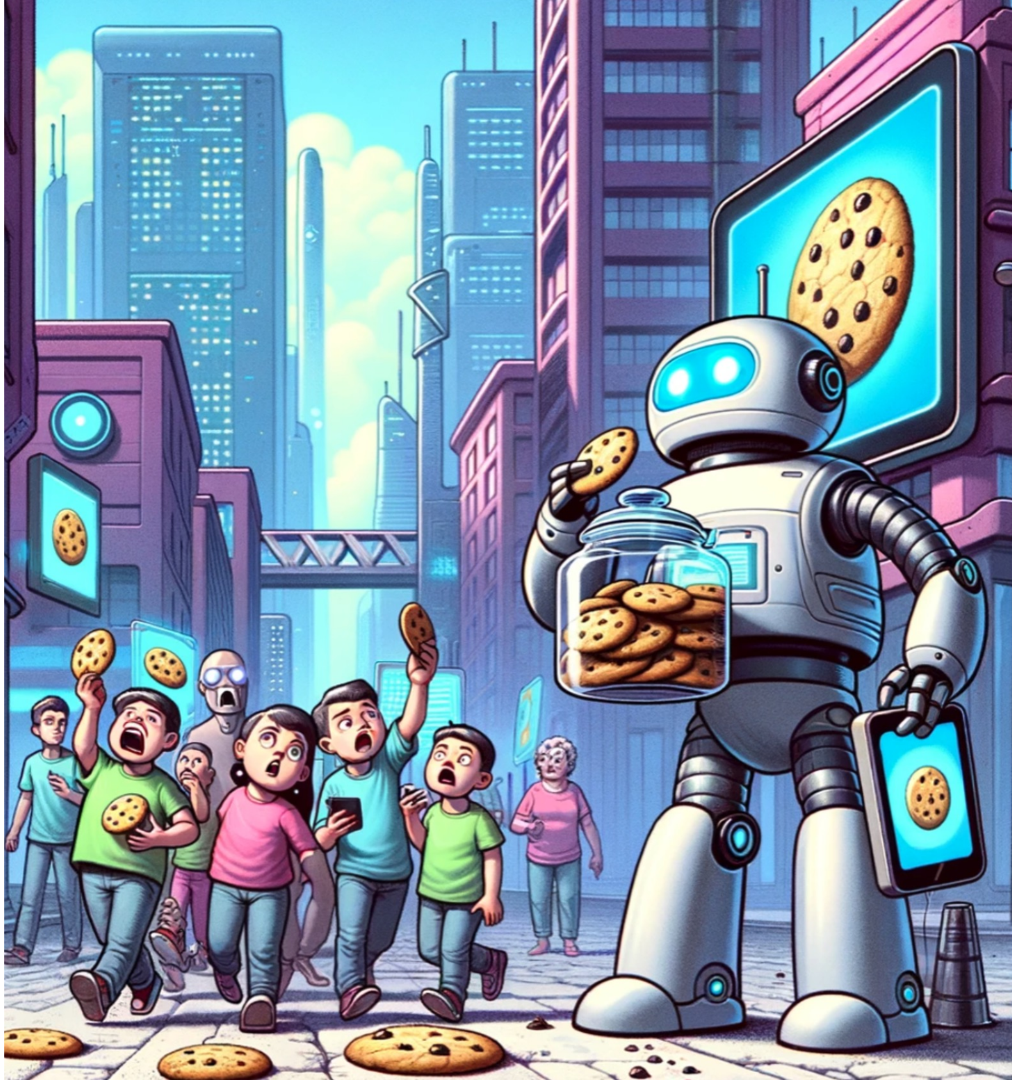
Ryan Dew

The Wharton School
University of Pennsylvania

Joint work with Anya Schetkina and Nicolas Padilla

The Cookie-free Future

- For the past 10+ years, individual-level trackability has been central to measuring marketing efficacy



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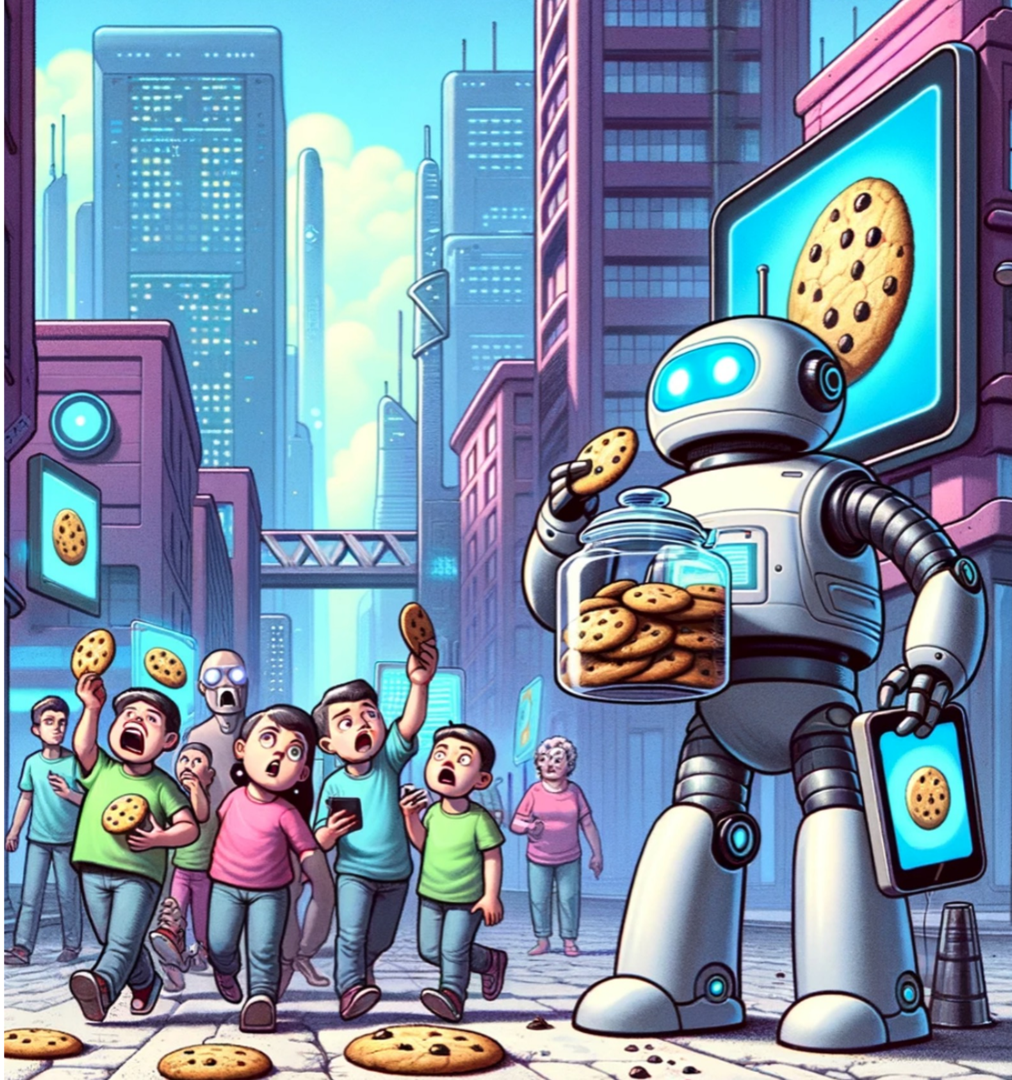

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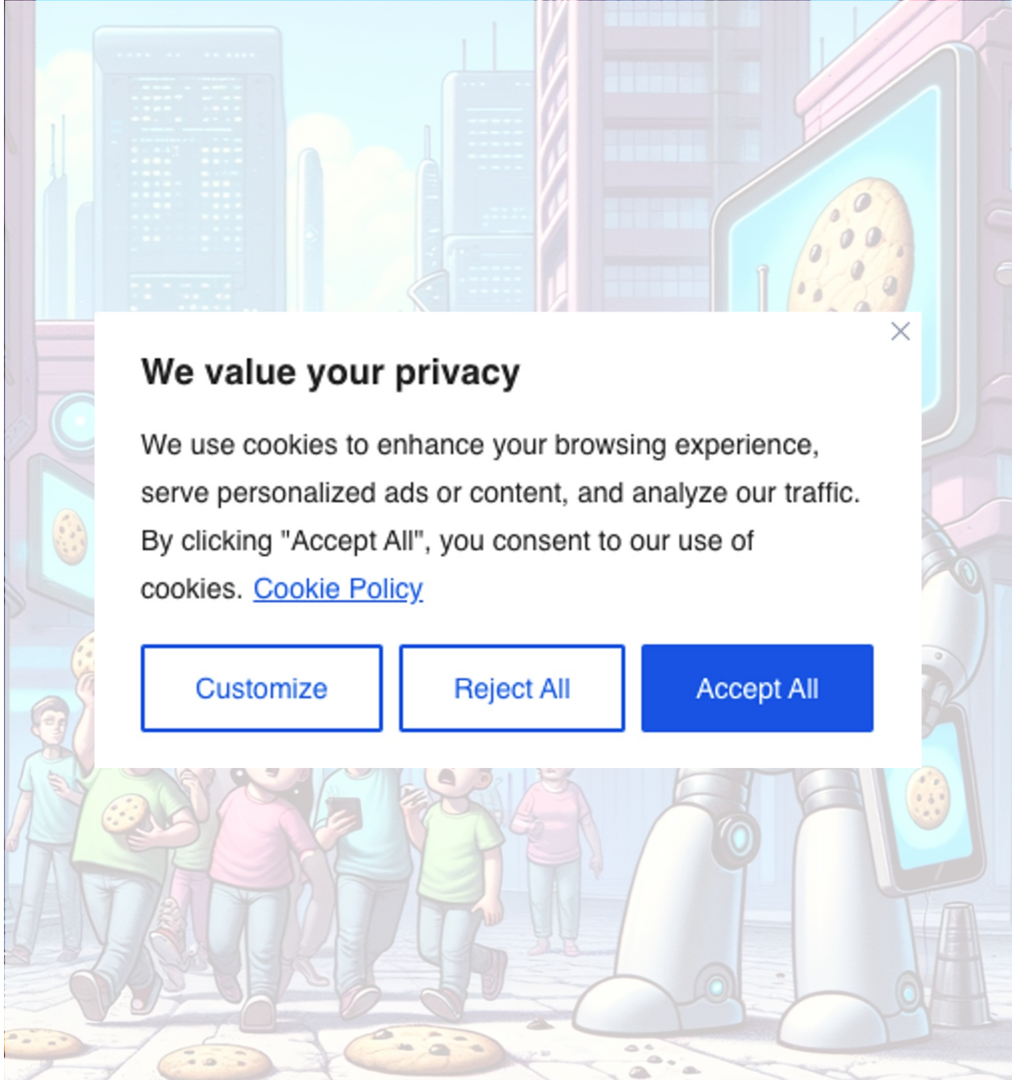

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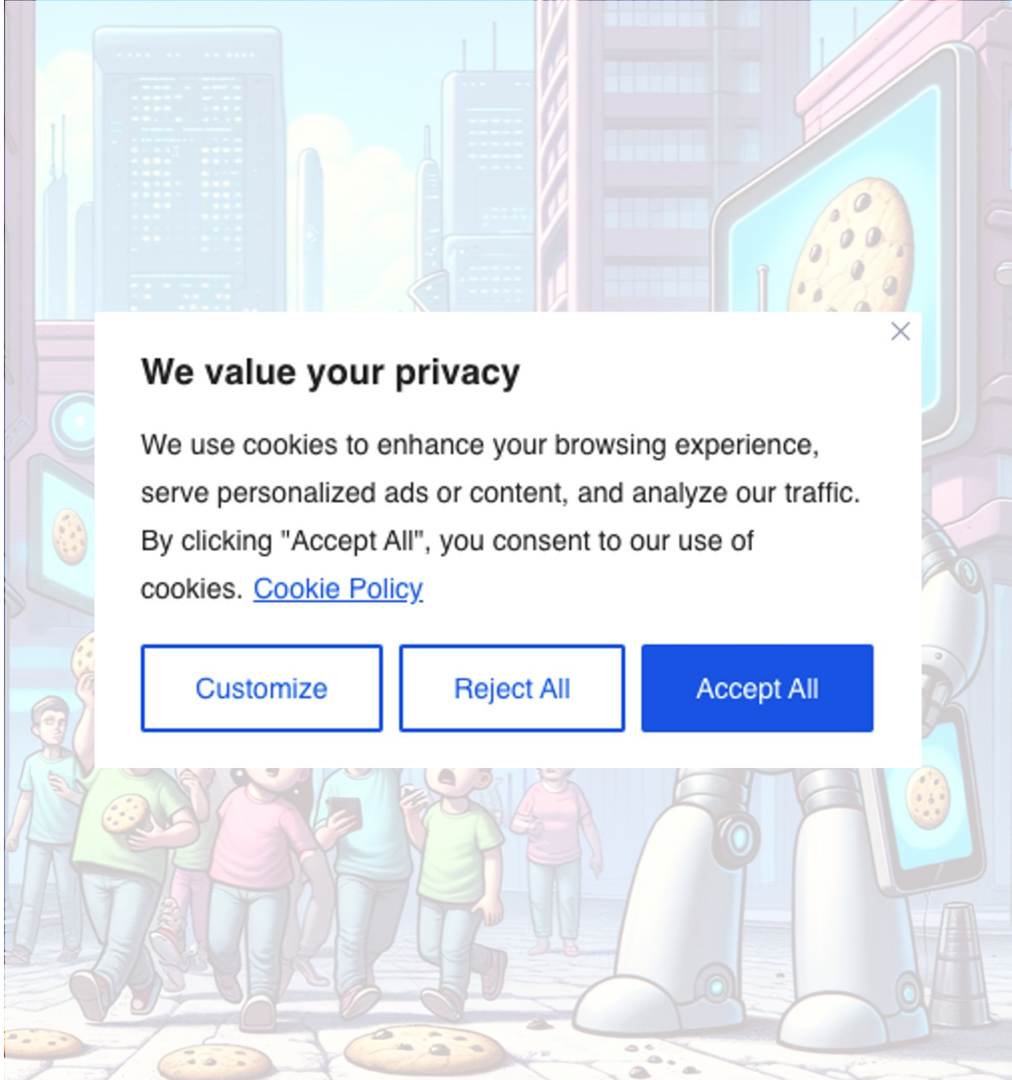
- Now? Gone!
- Result: huge resurgence in interest in models based on **aggregate data**




THE
RETURN
OF THE
MARKETING MIX MODEL
PRODUCT
PLACE
PLACE
PROMOTION

arXiv > stat > arXiv:2106.03322

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Statistics > Applications

[Submitted on 7 Jun 2021 (v1), last revised 5 Sep 2021 (this version, v3)]

Bayesian Time Varying Coefficient Model with Applications to Marketing Mix Modeling

Edwin Ng, Zhishi Wang, Athena Dai

Both Bayesian and varying coefficient models are very useful tools in practice as they can be used to model parameter heterogeneity in a generalizable way. Motivated by the need of enhancing Marketing Mix Modeling at Uber, we propose a Bayesian Time Varying Coefficient model, equipped with a hierarchical Bayesian structure. This model is different from other time varying coefficient models in the sense that the coefficients are weighted over a set of local latent variables following certain probabilistic distributions. Stochastic Variational Inference is used to approximate the posteriors of latent variables and dynamic coefficients. The proposed model also helps address many challenges faced by traditional MMM approaches. We used simulations as well as real world marketing datasets to demonstrate our model superior performance in terms of both accuracy and interpretability.

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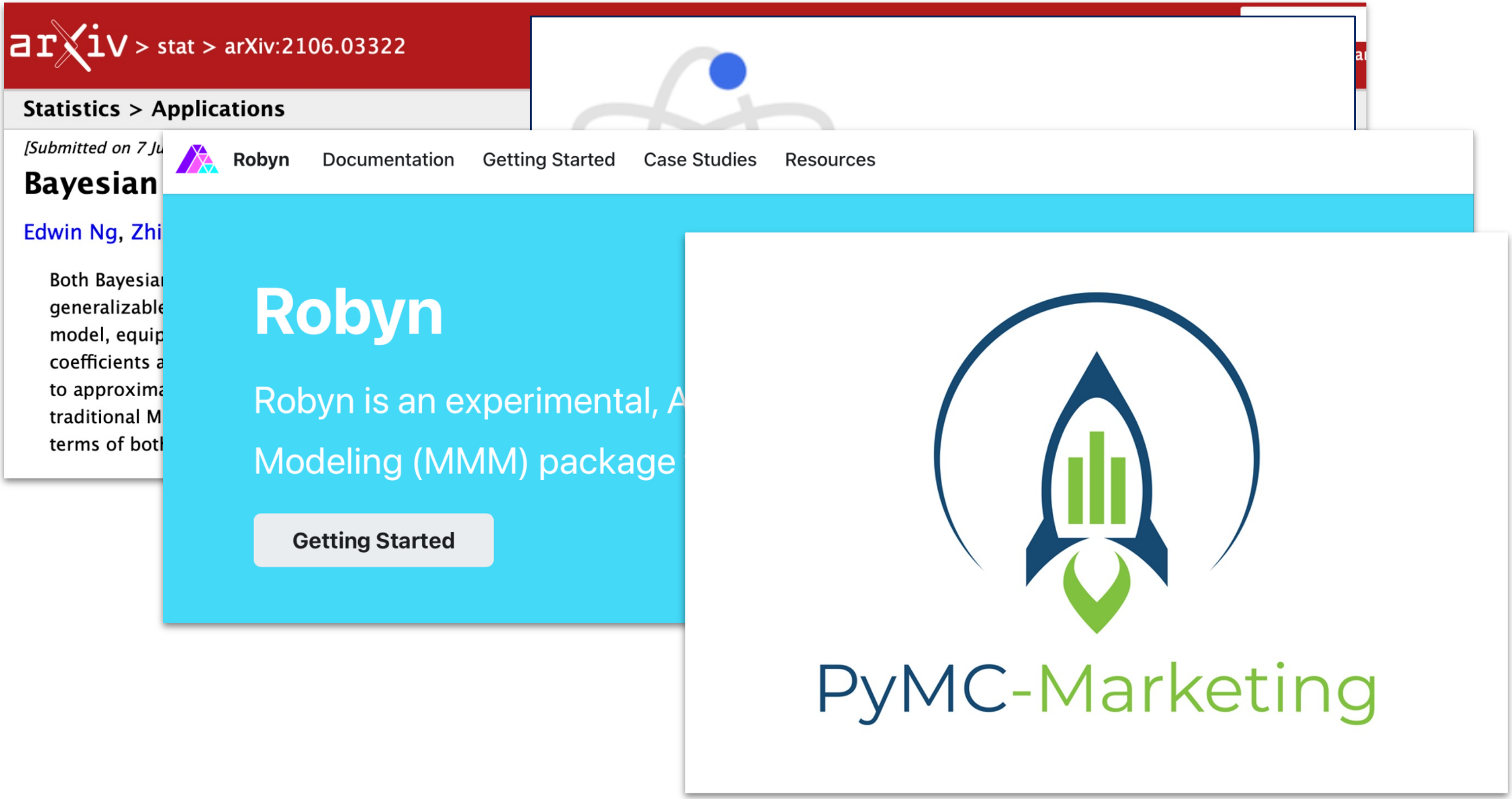
Robyn Documentation Getting Started Case Studies Resources

Robyn

Robyn is an experimental, AI/ML-powered and open sourced Marketing Mix Modeling (MMM) package from Meta Marketing Science.

Getting Started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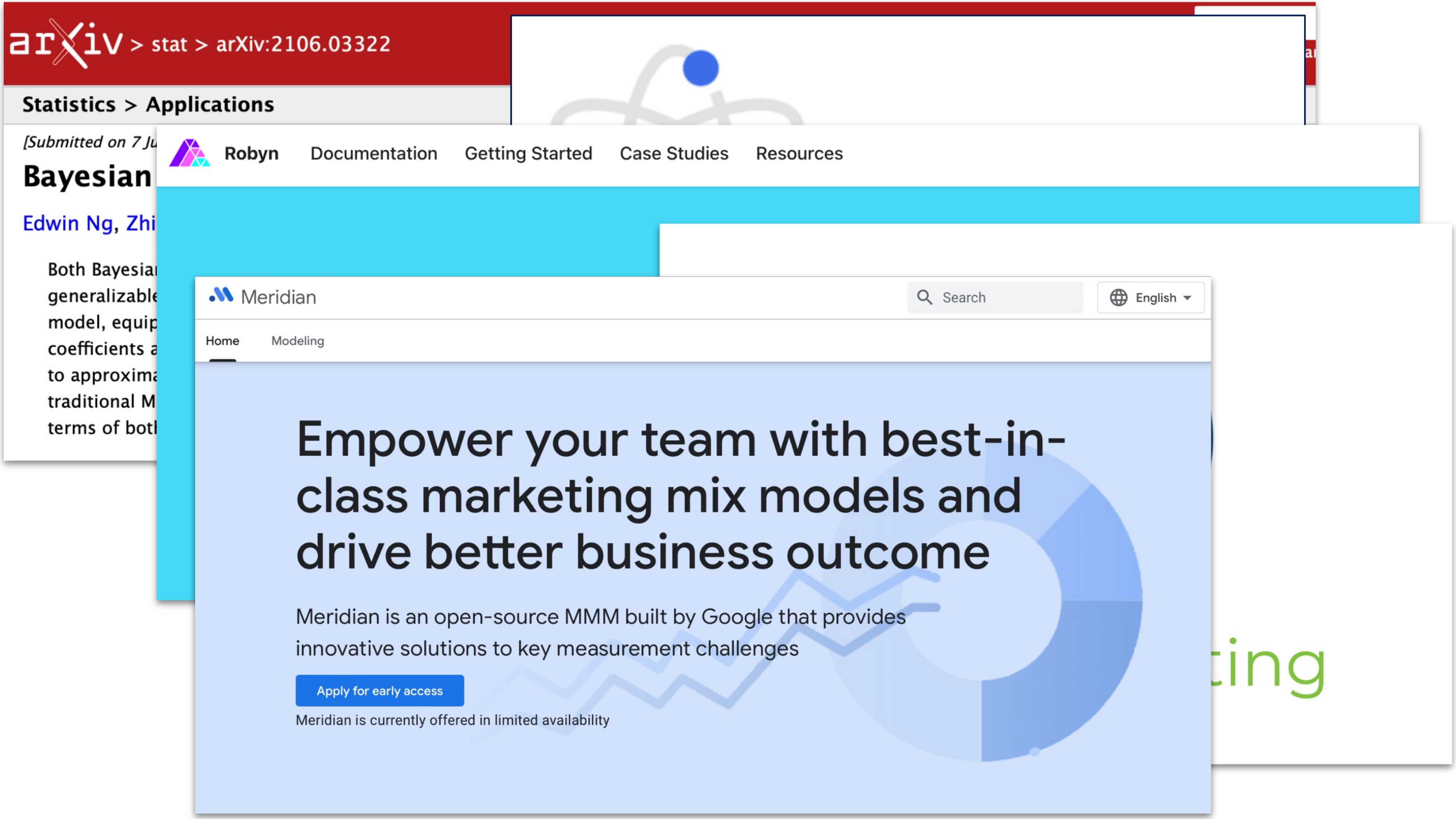

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Meridian
Search
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Modeling
Empower your team with best-in-class marketing mix models and drive better business outcome
Meridian is an open-source MMM built by Google that provides innovative solutions to key measurement challenges
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Marketing Mix Models

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  Borden (1964), Palda (1965), Bultez and Naert (1979), Little (1979), Winer (1979), ..., Hanssens et al. (2003), ...

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Note: Terminology

Throughout the talk, dynamic = time-varying

What’s new? Firepower

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Meridian

Wang et al. (2017), Jin et al. (2017), Sun et al. (2017), Zhang et al. (2023)

$$
\begin{aligned}
y_{g,t} = \mu_t + \tau_g + \sum_{c=1}^{C} \gamma_{g,c} z_{g,t,c} \\
+ \sum_{m=1}^{M} \beta_{g,m} HillAdstock \left(\left\{ x_{g,t-s,m} \right\}_{s=0}^{L} ;\ \alpha_m, ec_m, slope_m \right) \\
+ \sum_{n=1}^{N} \beta_{g,n}^{(rf)} Adstock \left(\left\{ r_{g,t-s,n} \cdot Hill \left(f_{g,t-s,n};\ ec_n^{(rf)},\ slope_n^{(rf)} \right) \right\}_{s=0}^{L} ;\ \alpha_n^{(rf)} \right) \\
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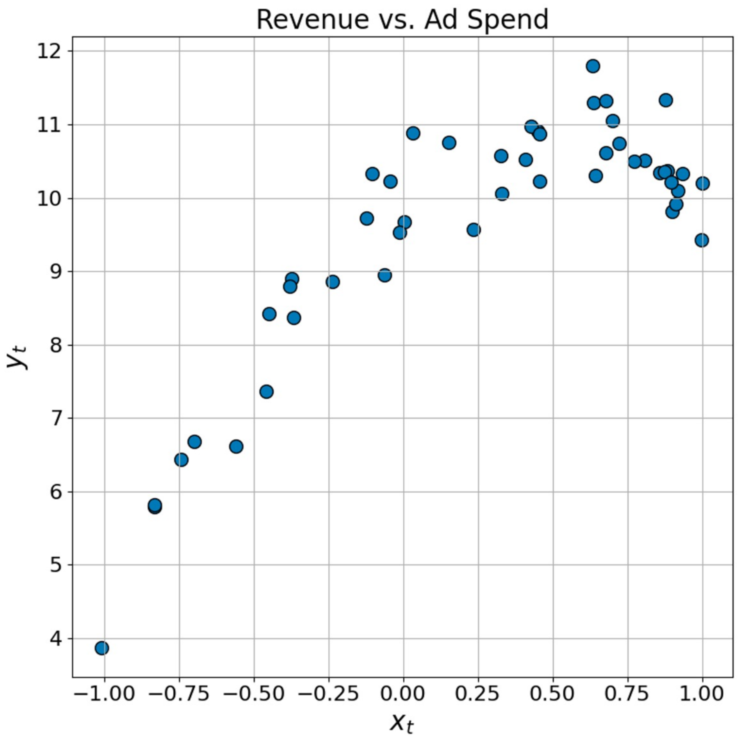
Uber’s Orbit

Ng et al., (2021)

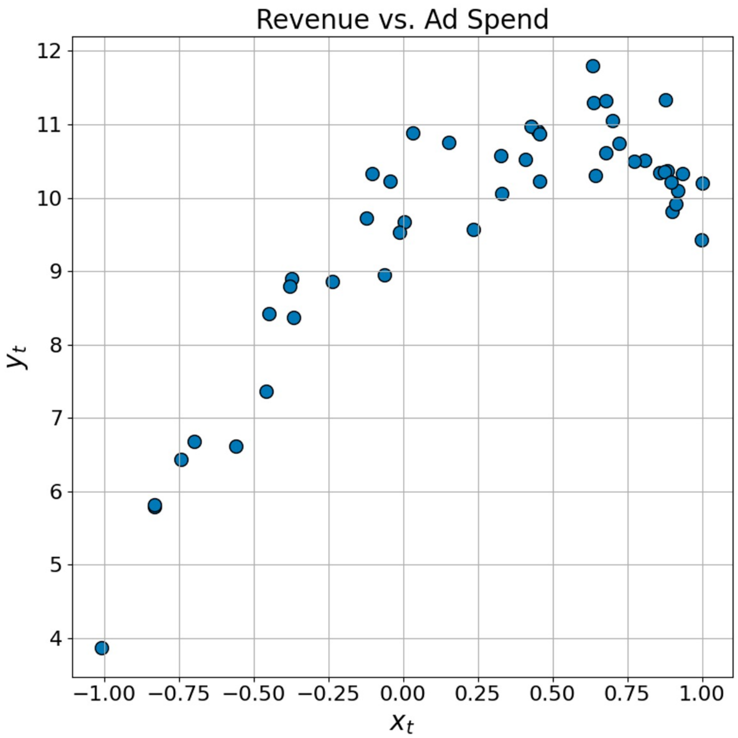
$$ln(\hat{y}_t) = l_t + s_t + \sum_{p=1}^{P} ln(x_{t,p})\beta_{t,p}$$

$$\beta_{t,p} = \sum_{j} w_j(t) \cdot b_{j,p},$$

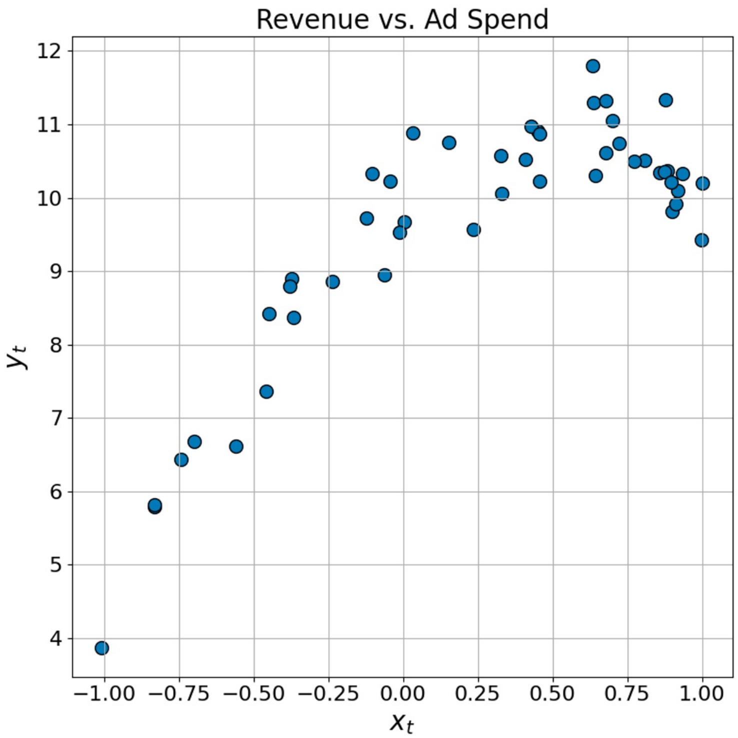
$$w_j(t) = k(t, t_j) / \sum_{i=1}^{J} k(t, t_i),$$



Revenue vs. Ad Spend
y_t
x_t
12
11
10
9
8
7
6
5
4
−1.00
−0.75
−0.50
−0.25
0.00
0.25
0.50
0.75
1.00



Surely this is nonlinear, right…?



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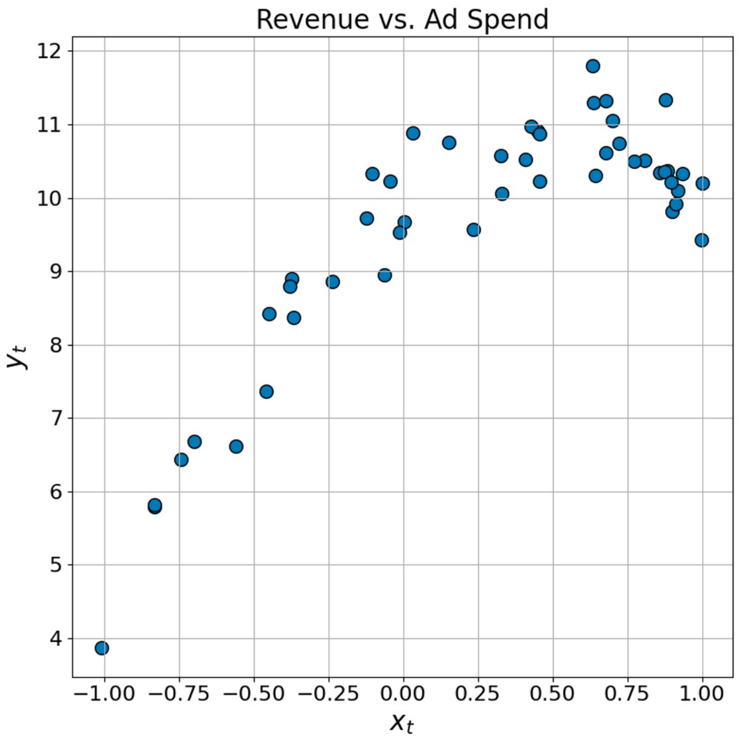

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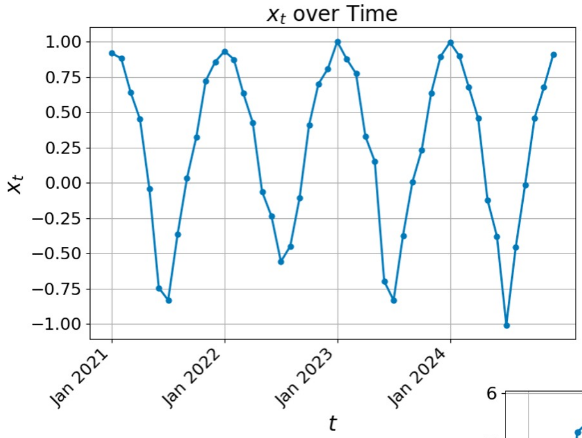

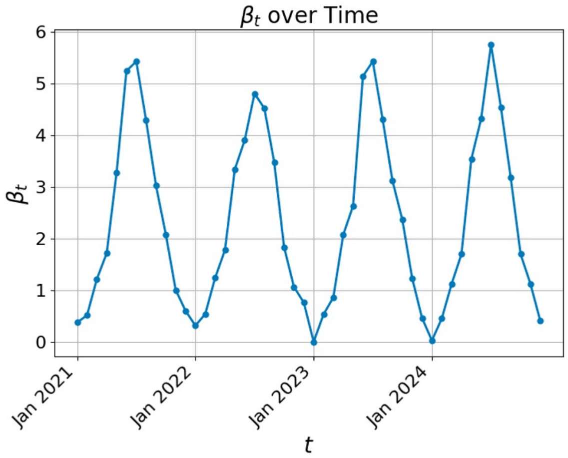

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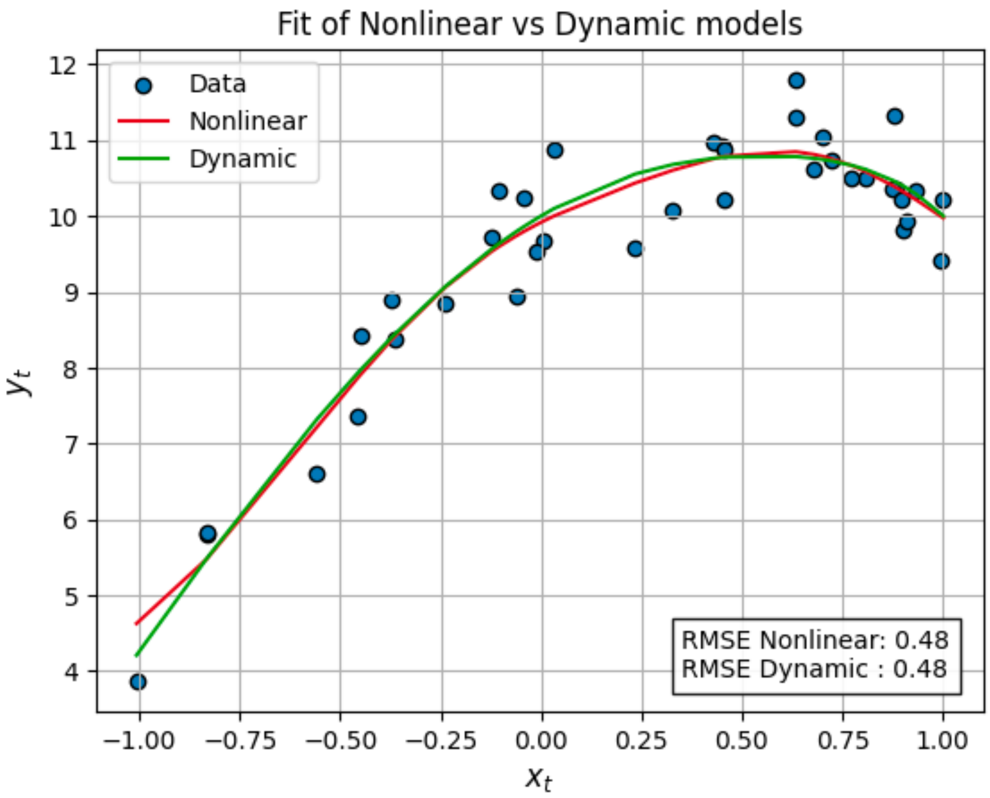
Identical Fit



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3. Problems are exacerbated under common managerial practices, like **autoregressive decision-making**
4. Similarly fitting models can have **fundamentally different implications** in terms of optimal decision-making

(A little) Math

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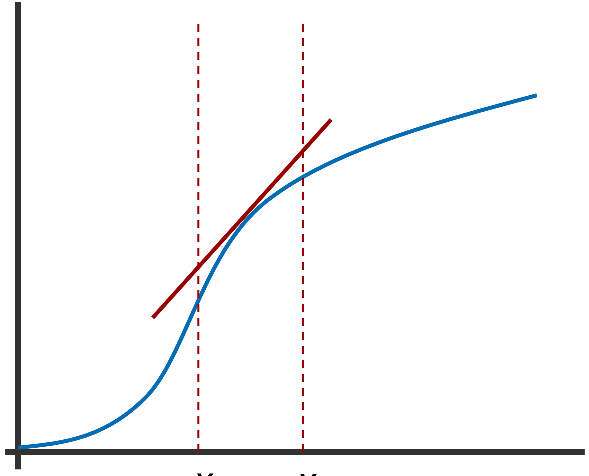

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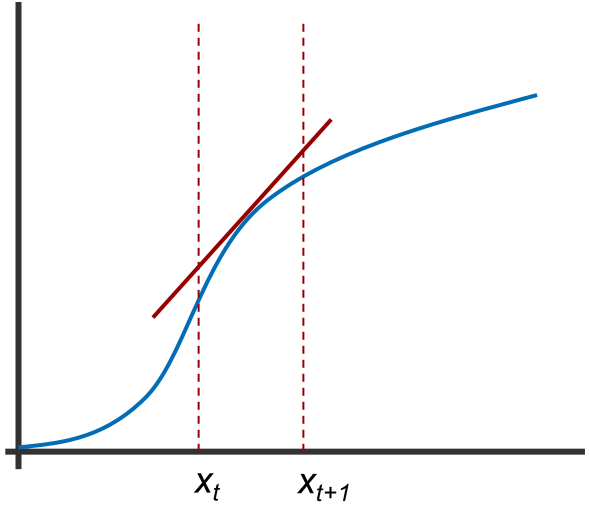
- When will β_t be smooth ("forecastable")? If f is smooth and x_t and x_{t+1} are close together!



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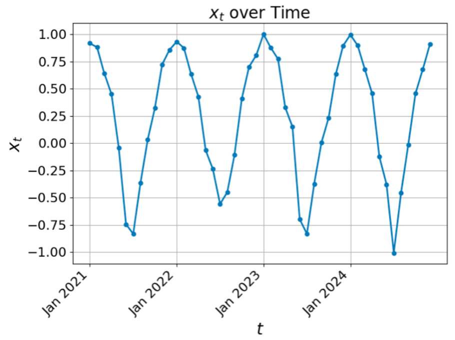

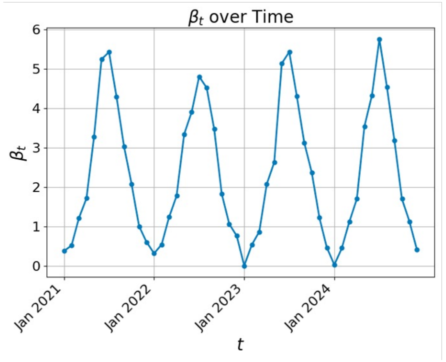

Simulations

When does conflation *actually* happen?

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Four types of simulations:

1. Flexible nonlinear response
$$y_t = f(x_t) + \varepsilon_t$$

2. Dynamic coefficients, linear (or log-linear) model
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3. Nonlinear response, parametric hill function
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Gaussian processes
Two important levers:
- Smoothness
- Amplitude

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Gaussian processes: a Bayesian nonparametric approach to modeling unknown functions

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$$k(x, x') = \eta^2 \exp\left\{-\frac{(x - x')^2}{2\rho^2}\right\}$$

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$$f(x) \sim \mathcal{GP}(m(x), k(x, x'))$$

$$\uparrow\downarrow$$

$$f(x_1, \ldots, x_N) \sim \mathcal{N}(m(x_1, \ldots, x_N), K), \text{ s.t. } K_{ij} = k(x_i, x_j)$$

$$k(x, x') = \overbrace{\boxed{\eta^2}}^{\text{Amplitude}} \exp\left\{-\frac{(x - x')^2}{2\underbrace{\boxed{\rho^2}}_{\text{Lengthscale}}}\right\}$$

Primer: Gaussian Processes

Gaussian processes: a Bayesian nonparametric approach to modeling unknown functions

$$f(x) \sim \mathcal{GP}(m(x), k(x, x'))$$

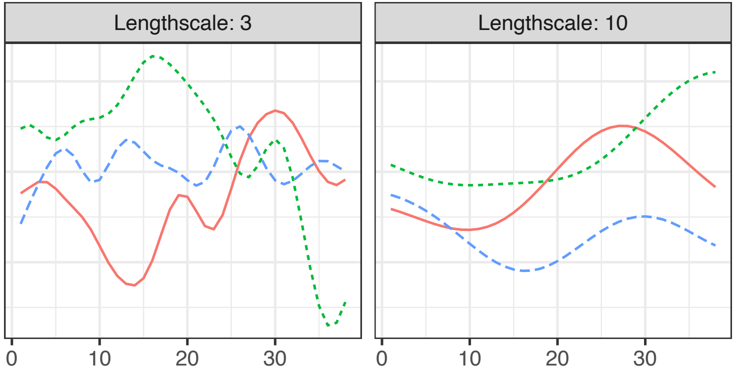
$$\uparrow\downarrow$$

$$f(x_1, \ldots, x_N) \sim \mathcal{N}(m(x_1, \ldots, x_N), K), \text{ s.t. } K_{ij} = k(x_i, x_j)$$

Amplitude

$$k(x, x') = \boxed{\eta^2} \exp\left\{-\frac{(x - x')^2}{\boxed{2\rho^2}}\right\}$$

Lengthscale



When does conflation *actually* happen?

Four types of simulations:

1. Flexible nonlinear response
$$y_t = \boxed{f(x_t)} + \varepsilon_t$$
2. Dynamic coefficients, linear (or log-linear) model
$$y_t = \boxed{\beta(t)} x_t + \varepsilon_t$$
3. Nonlinear response, parametric hill function
$$y_t = \mathrm{Hill}(x_t) + \varepsilon_t$$
4. Dynamic coefficients inherited from common parent
$$y_t = \beta(t)x(t) + \varepsilon_t, \; (\beta(t), x(t)) \sim \mathrm{Pa}(t)$$

Gaussian processes
Two important levers:
- Smoothness
- Amplitude

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3. Nonlinear response, parametric hill function

4. Dynamic c

Gaussian processes

Two important levers:

- Smoothness
- Amplitude

Other manipulated features:

- Autoregressive coefficient in x
- Noise in x's autoregressive process
- Variance of the error term

Simulation Results

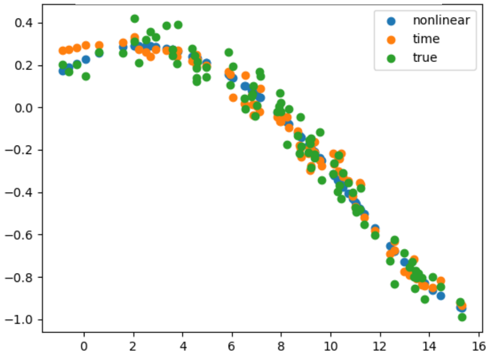
- For each simulation type, >300 settings, systematically varying the previously described factors, with 100 simulations per setting
- Fit both models (nonlinear and dynamic), measure conflation through validation RMSE

Examples

Nonlinear DGP

Smooth f, low noise

Data



Examples

Nonlinear DGP

Smooth f, low noise

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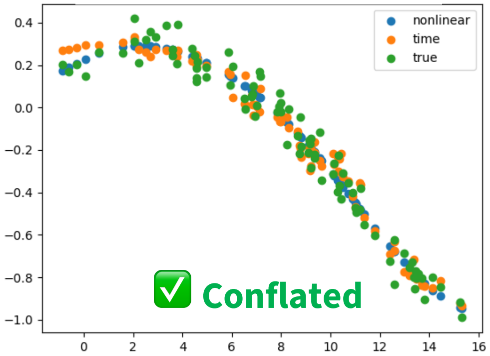
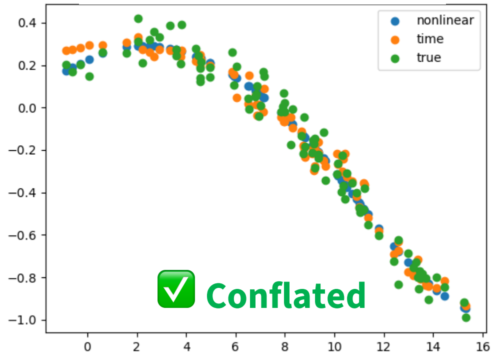


Examples

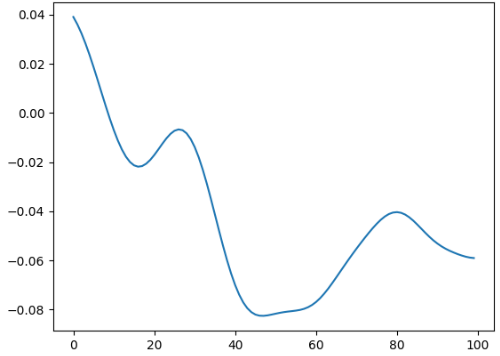
Nonlinear DGP

Smooth f, low noise

Data



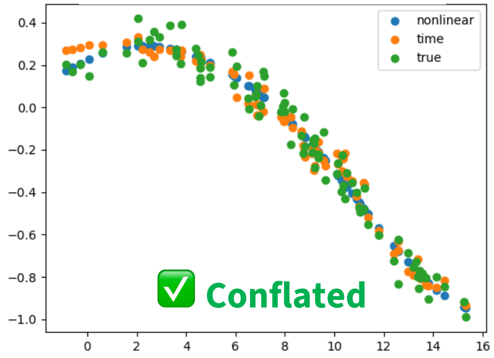
Implied $\beta(t)$

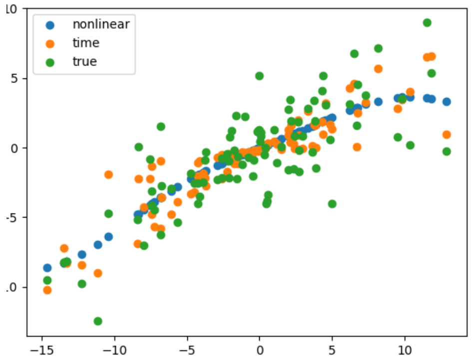


Examples

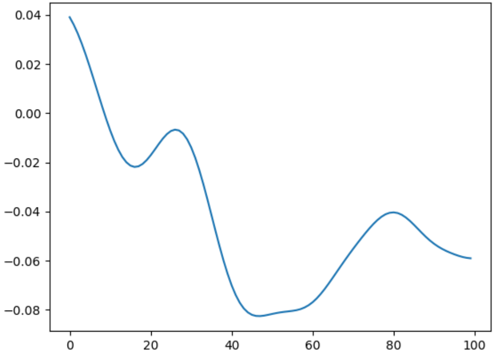
	Nonlinear DGP *Smooth f, low noise*	**Dynamic DGP** *Smooth f, low noise*

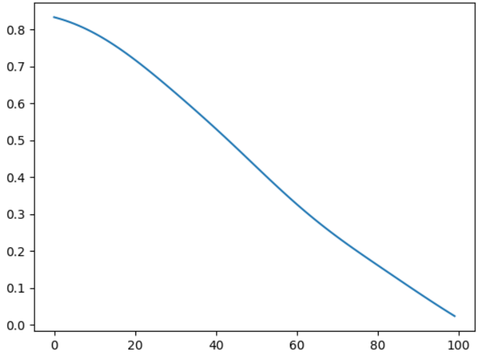
Data





Implied $\beta(t)$



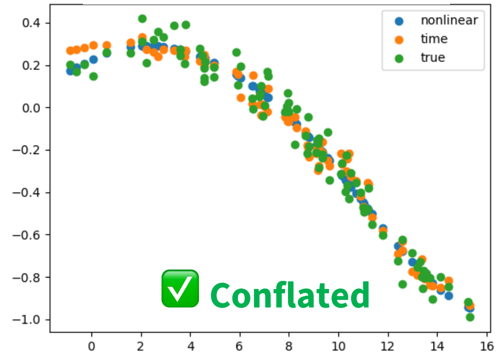


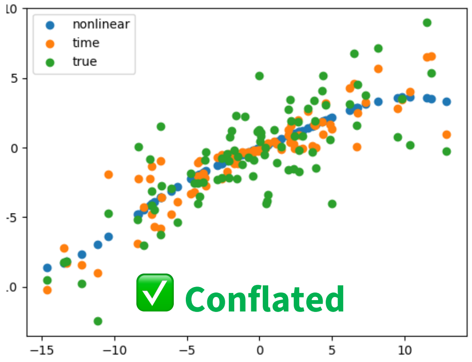
Examples

Nonlinear DGP
Smooth f, low noise

Dynamic DGP
Smooth f, low noise

Data





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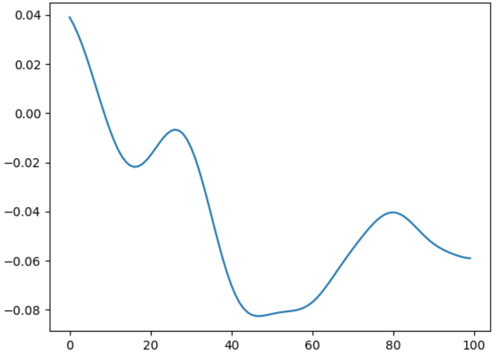
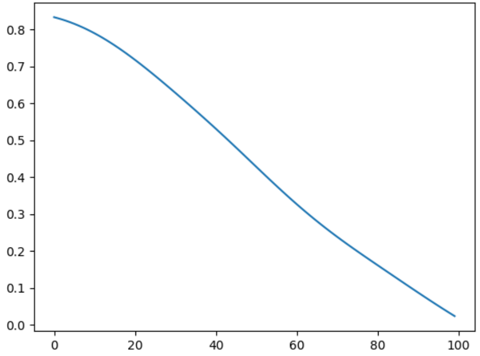
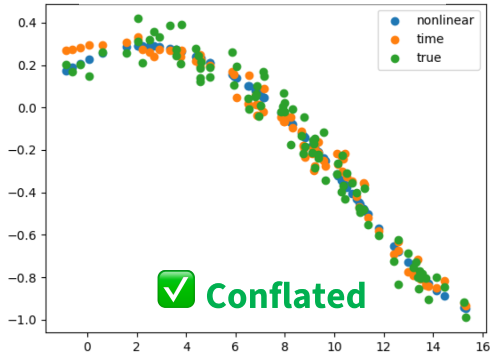
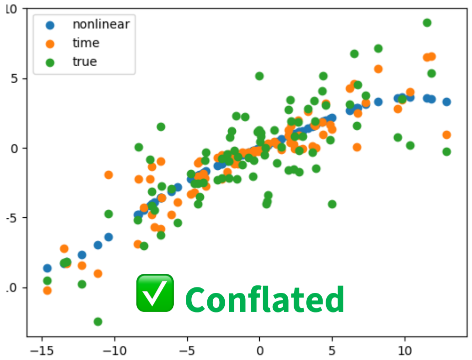
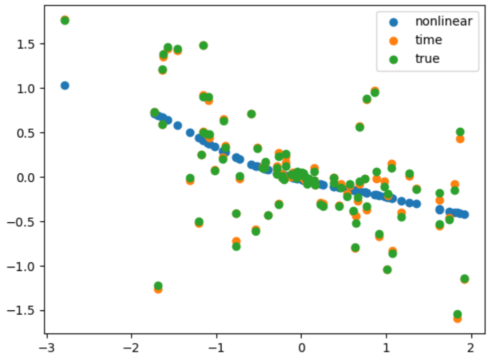
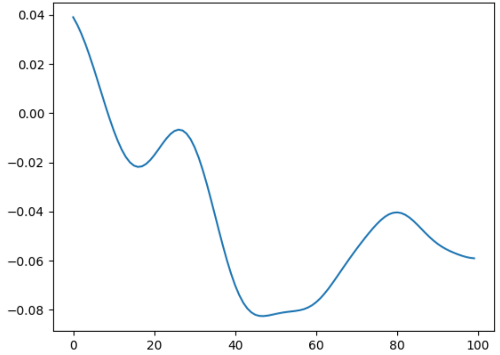
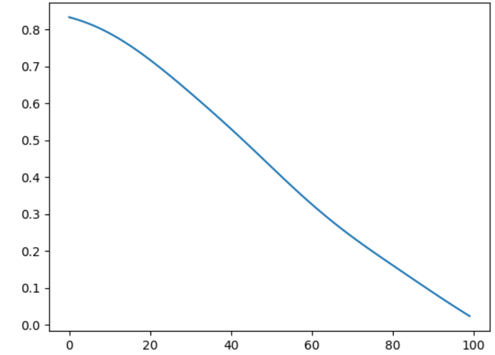
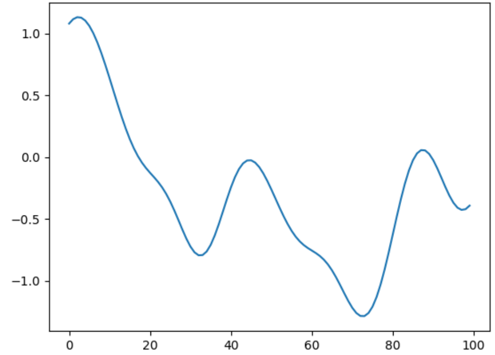




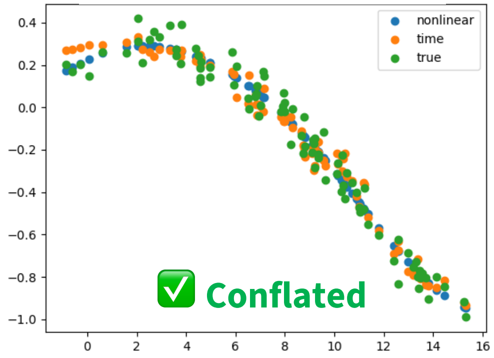
Examples

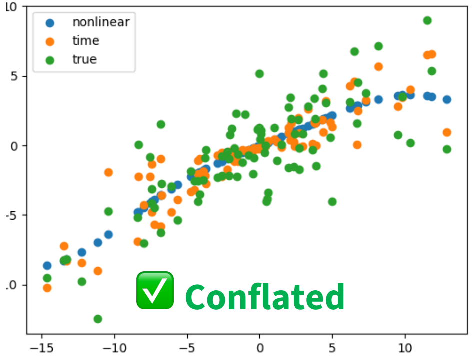
	Nonlinear DGP *Smooth f, low noise*	**Dynamic DGP** *Smooth f, low noise*	**Dynamic DGP** *Less smooth f, low noise*
Data			
Implied $\beta(t)$			

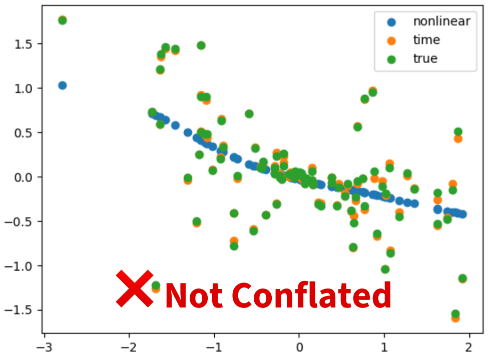
Examples

	Nonlinear DGP	**Dynamic DGP**	**Dynamic DGP**
	Smooth f, low noise	*Smooth f, low noise*	*Less smooth f, low noise*

Data







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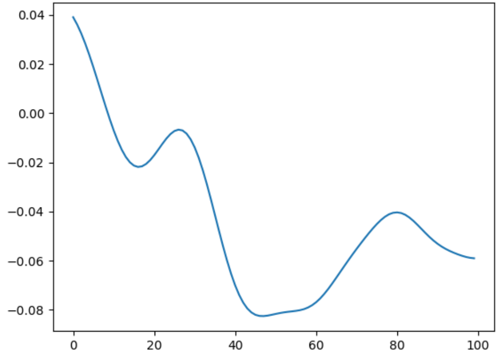

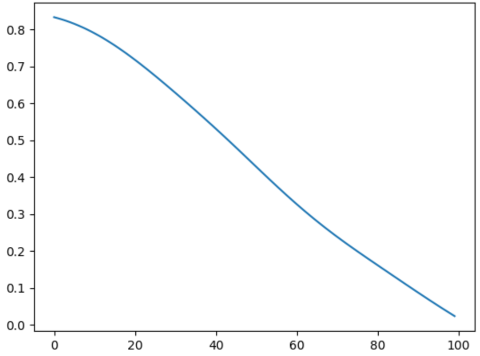

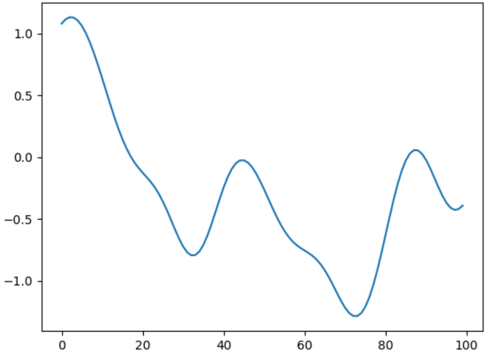

Simulation Results

- Systematically vary the previously described factors, with 100 simulations per setting
- Fit both models (nonlinear and dynamic), measure conflation through validation RMSE

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Main result: huge prevalence of conflation

- Under the nonlinear DGP, **82%** exhibited some conflation, with **23% exhibiting major conflation** *(defined as >25% of simulations conflated)*
- Under the time-varying DGP, **80%** exhibited some conflation, with **27% exhibiting major conflation**

Diving Deeper

DV: % Conflated Simulations

Diving Deeper

DV: % Conflated Simulations

Variable	Level	Nonlinear DGP Coef	Nonlinear DGP $P(>\|t\|)$	Dynamic DGP Coef	Dynamic DGP $P(>\|t\|)$
Amplitude, f:	Low	-	-	-	
	Middle	-0.06	0.94	2.94	0.01
	High	-0.11	0.88	8.99	0.00
Smoothness, f:	Low	-	-	-	
	Middle	9.99	0.00	3.44	0.00
	High	19.43	0.00	8.10	0.00
AR coef, x:	Low	-	-	-	
	Middle	0.81	0.28	1.05	0.36
	High	2.66	0.00	4.77	0.00
Variance, x:	Low	-	-	-	
	Middle	-0.16	0.83	5.80	0.00
	High	0.07	0.92	11.66	0.00
Noise, y	Low	-	-	-	
	Middle	7.60	0.00	6.69	0.00
	High	14.81	0.00	20.25	0.00
	Very High	24.02	0.00	40.19	0.00

Table 1: Simulation Results: DV = Percentage Conflation; Intercept omitted for clarity.

Diving Deeper

DV: % Conflated Simulations

Conflation more likely with...

- Noisier data (i.e., ϵ_t)

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Diving Deeper

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Conflation more likely with…

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Decisions are often autocorrelated!

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Even worse with AdStock

Under the <u>nonlinear DGP</u> with AdStock, **93%** exhibited some conflation,

with **37% exhibiting major conflation**

(previously: 82% and 23%)

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Under the nonlinear DGP with AdStock, **93%** exhibited some conflation,

with **37% exhibiting major conflation**

(previously: 82% and 23%)

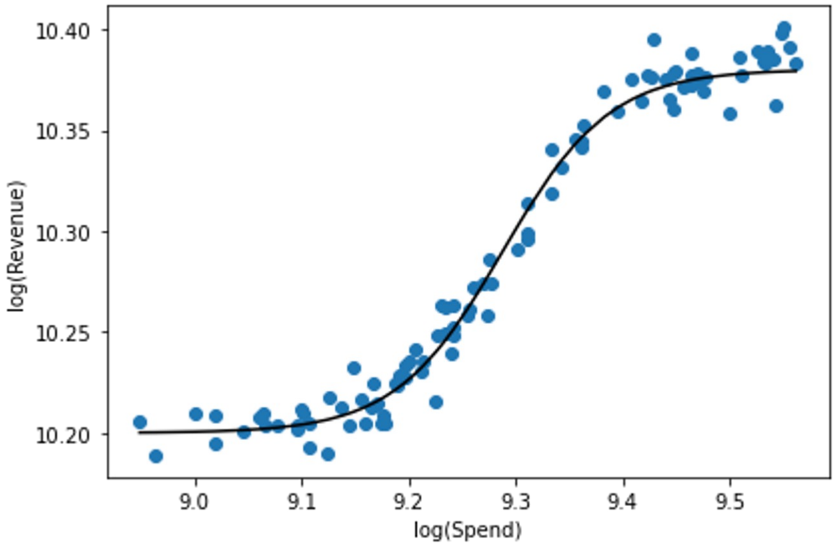
Under the time-varying DGP with AdStock, **87%** exhibited some conflation,

with **52% exhibiting major conflation**

(previously: 80% and 27%)

Implications

One last simulation…



(or from roughly $8,000 to $14,000)

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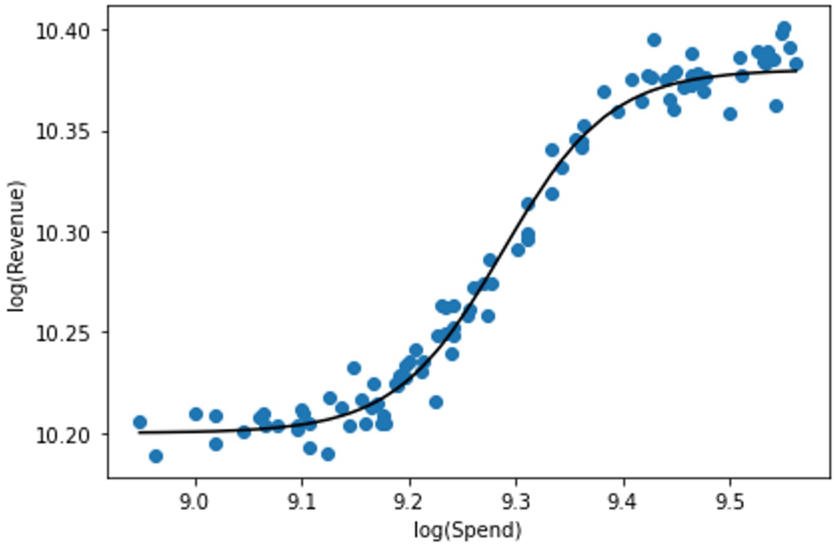

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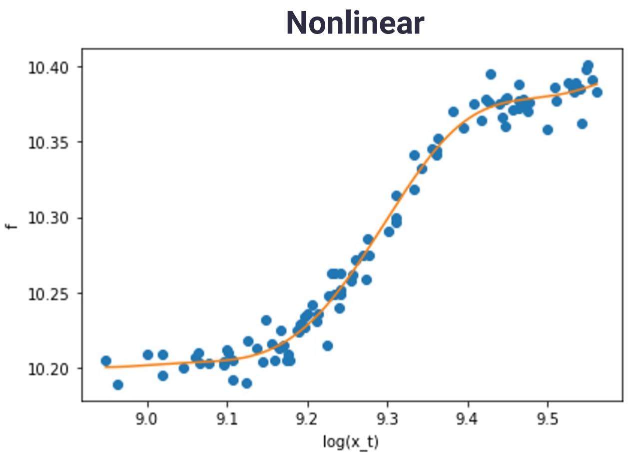

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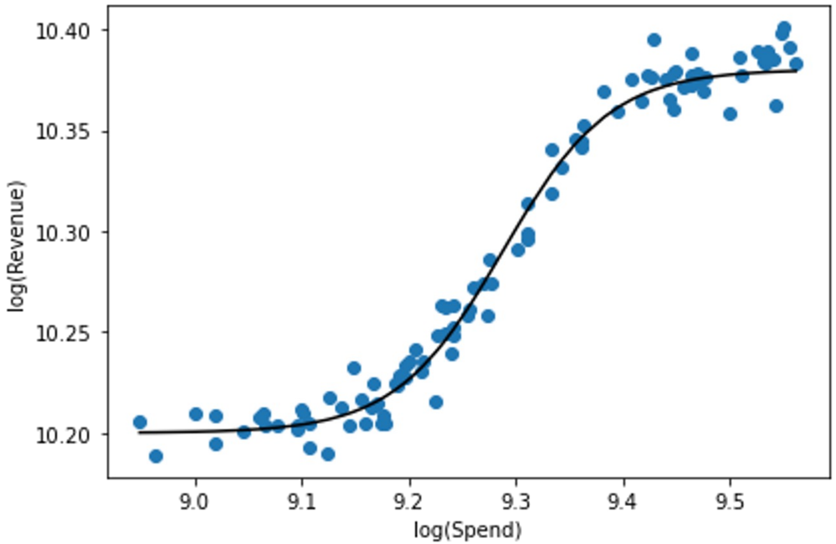

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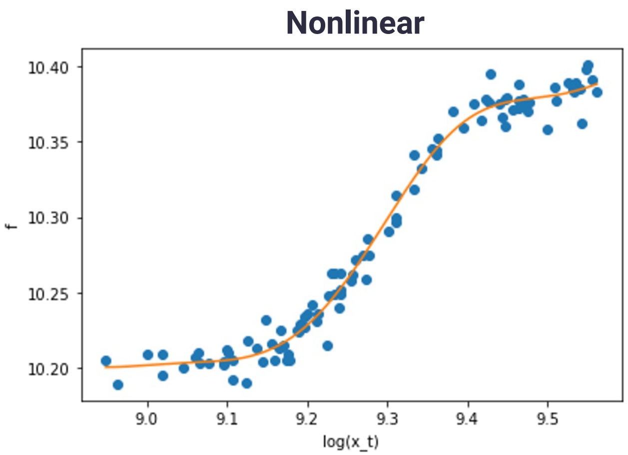

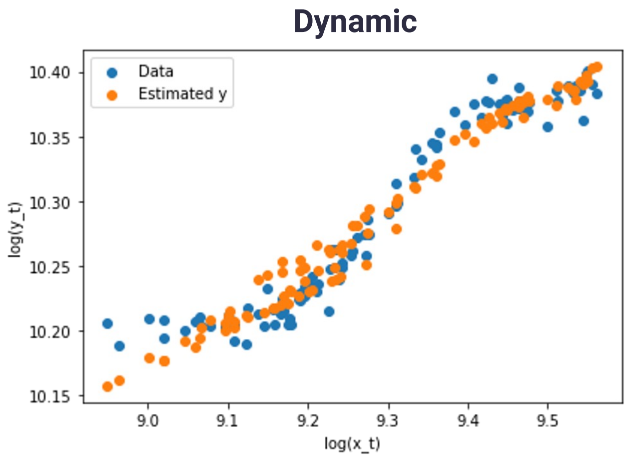

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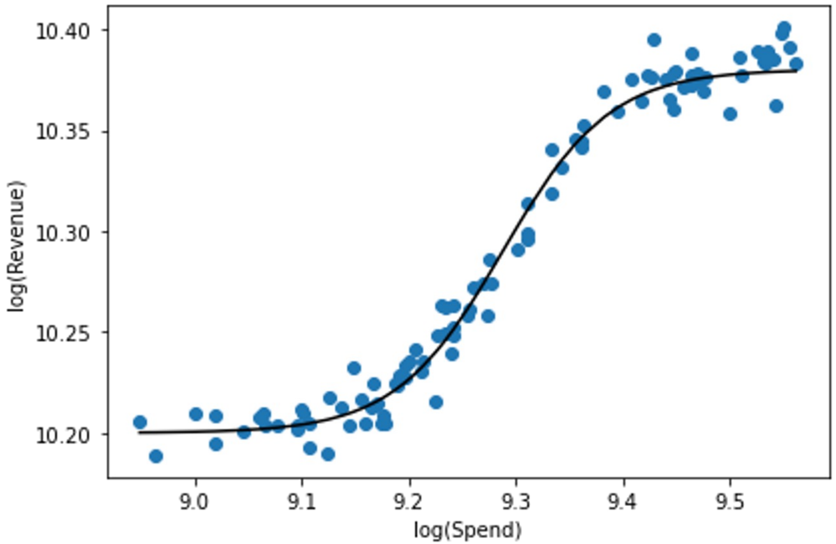

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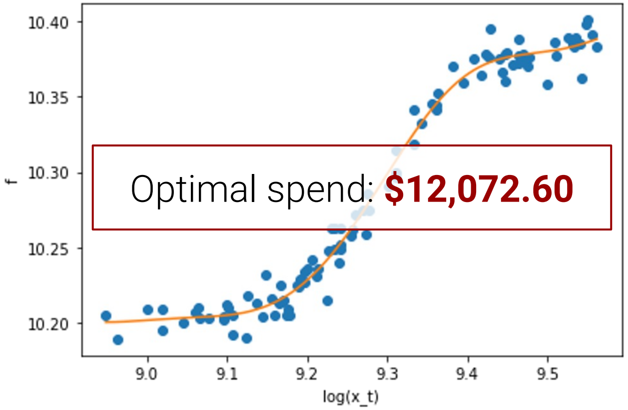
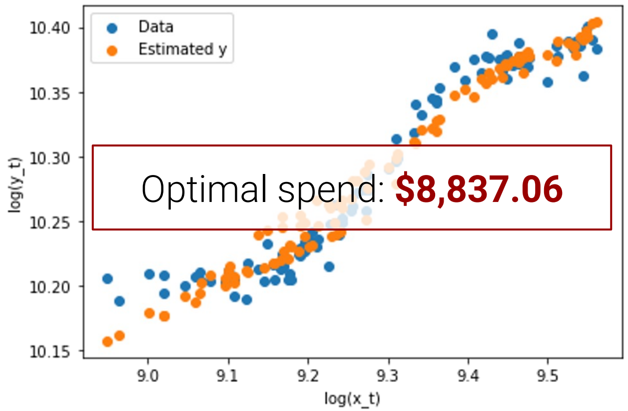
Nonlinear

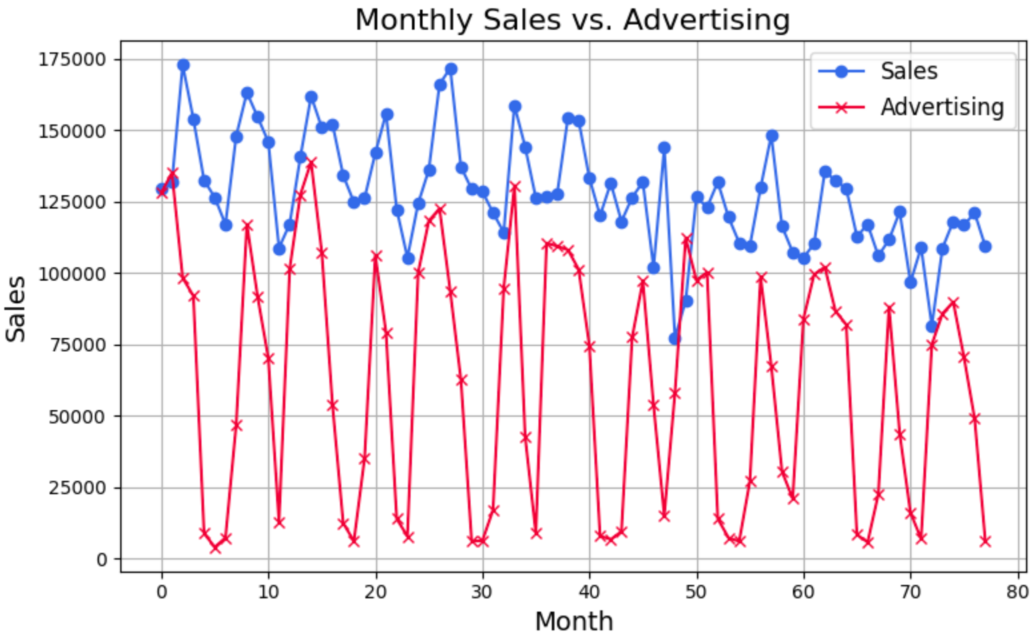


Dynamic



Application: The Classic Lydia Pinkham Dataset

Sales and advertising of Lydia Pinkham's herbal products, monthly, 1954-1960 (Palda, 1964)



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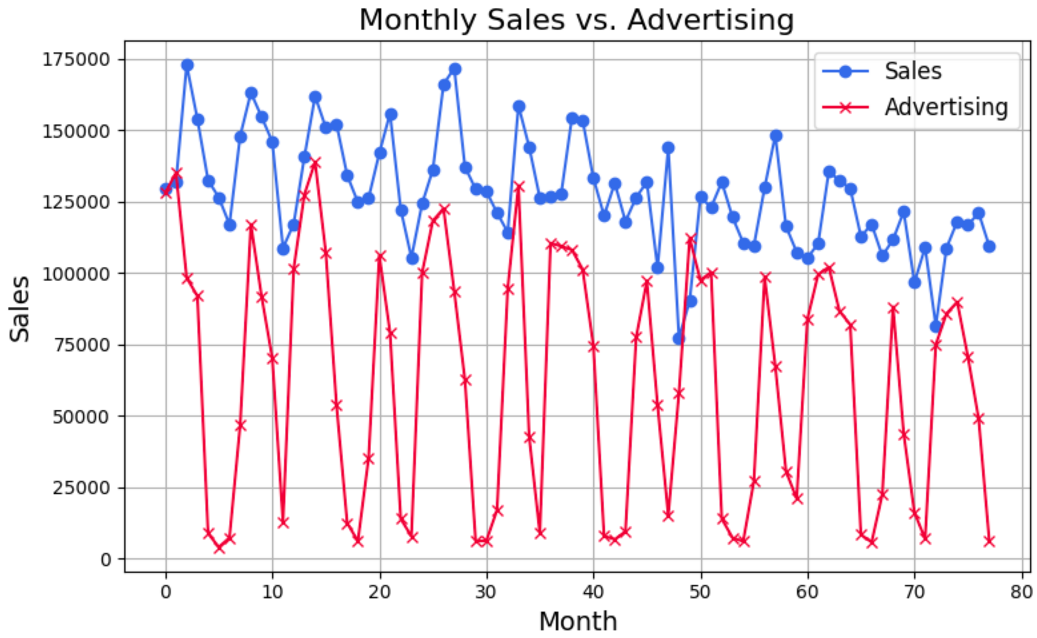

Conflation

Fit both nonlinear and dynamic models, using AdStock with carryover $\alpha = 0.7$ and $L = 13$ (Bultez and Naert, 1979)

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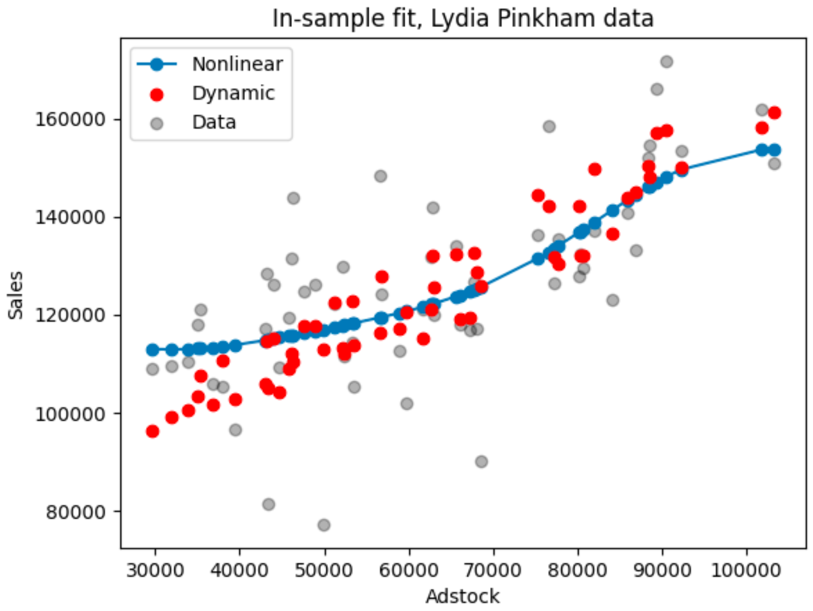

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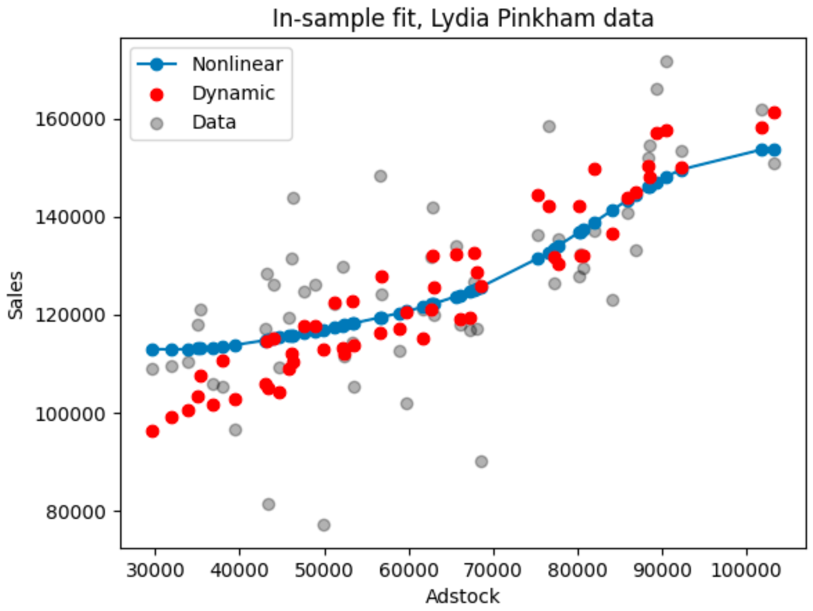

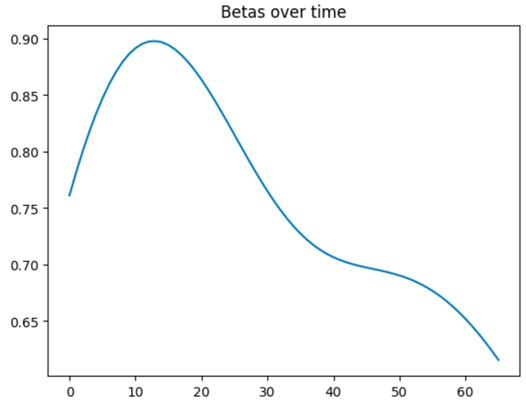

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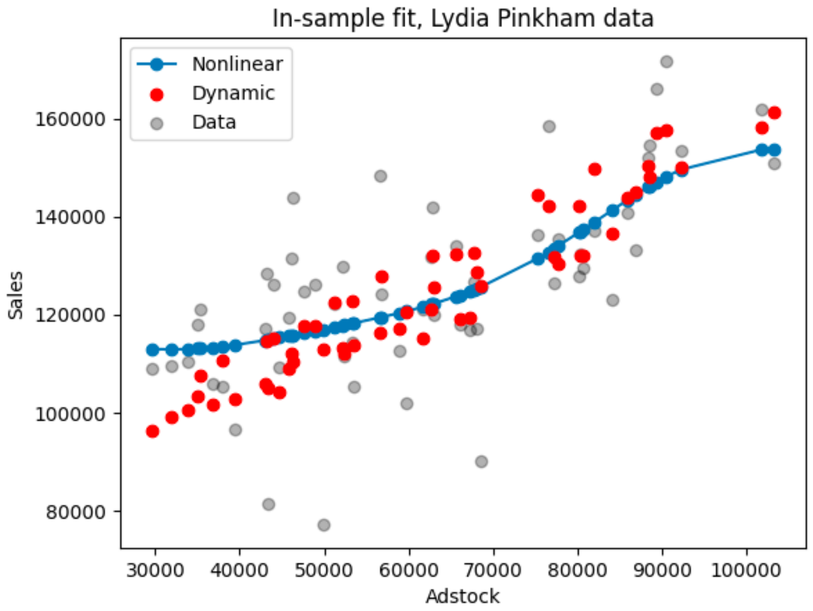

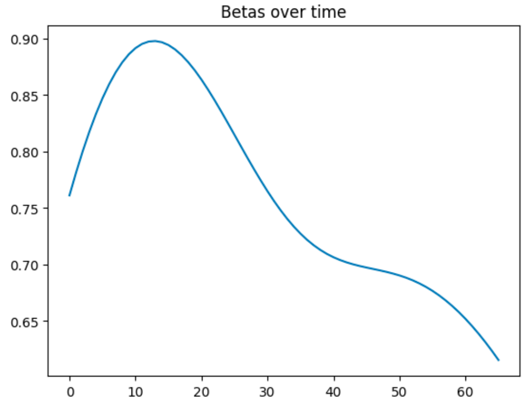

95% posterior predictive MSE intervals:

Nonlinear: [126.80, 174.78]

Dynamic: [93.31, 127.18]

Returns from Advertising

$$\text{Return}[T_1, T_2] = \sum_{t>T} \hat{y}_t(x_{[T_1,T_2]} = x_{\text{True}}) - \hat{y}_t(x_{[T_1,T_2]} = 0)$$

Returns from Advertising

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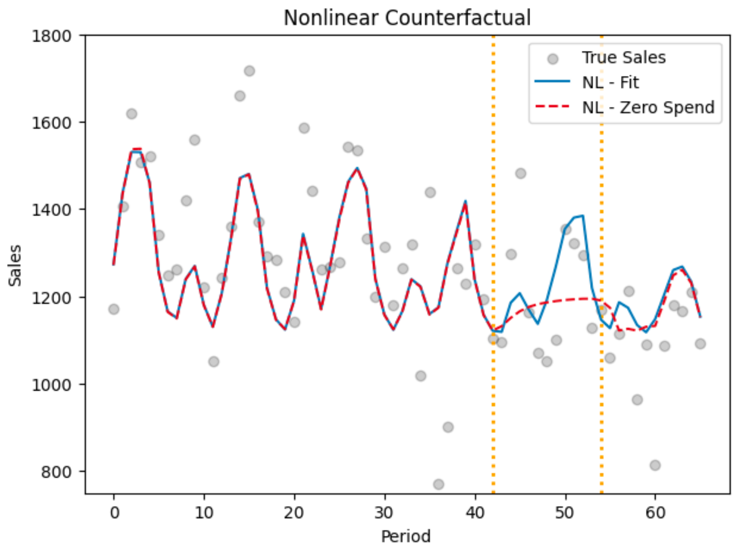

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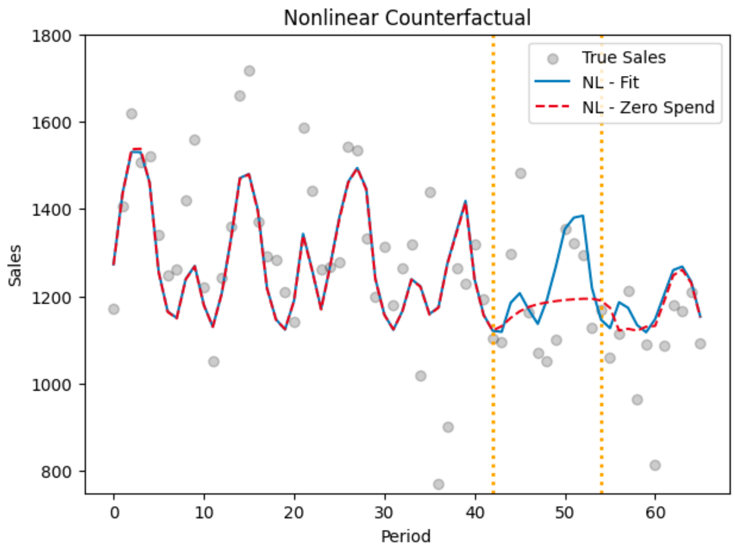

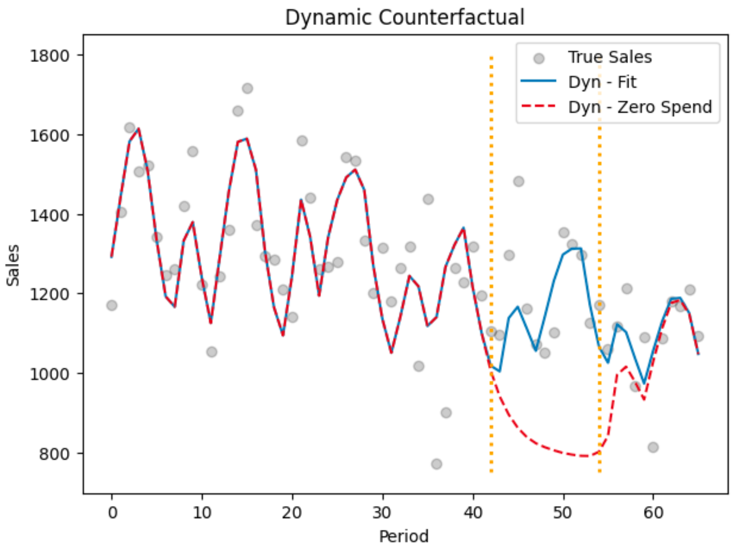

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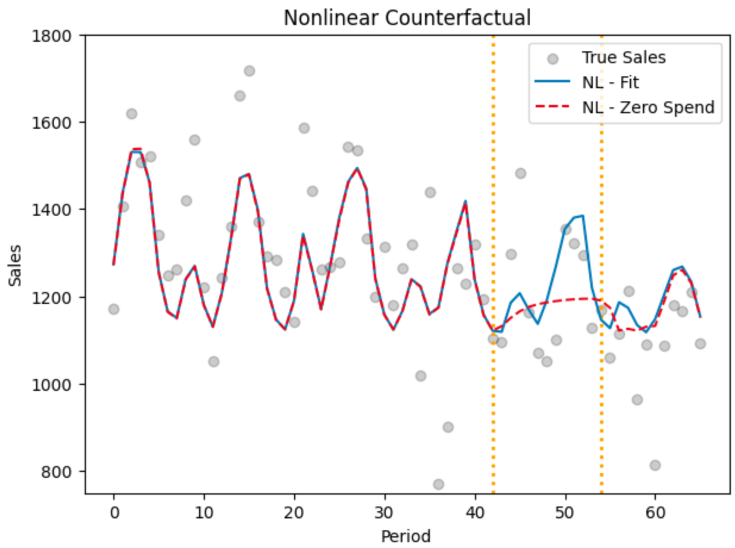
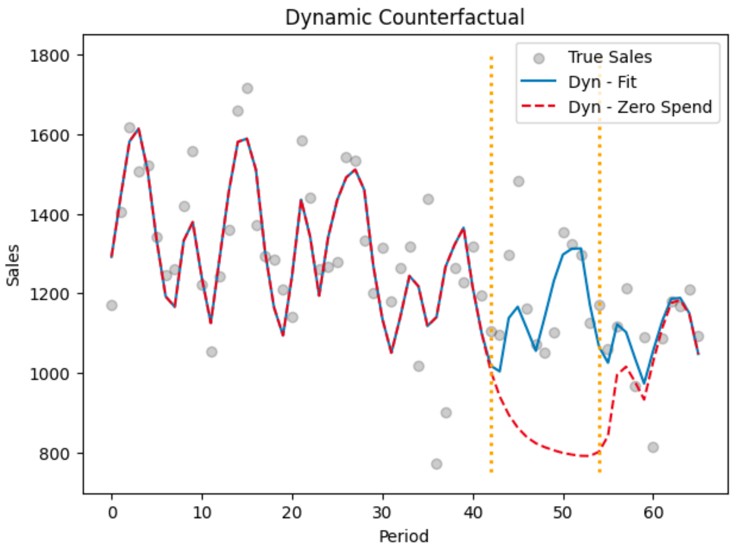


Estimated revenue: **$66,427**



Estimated revenue: **$468,832**

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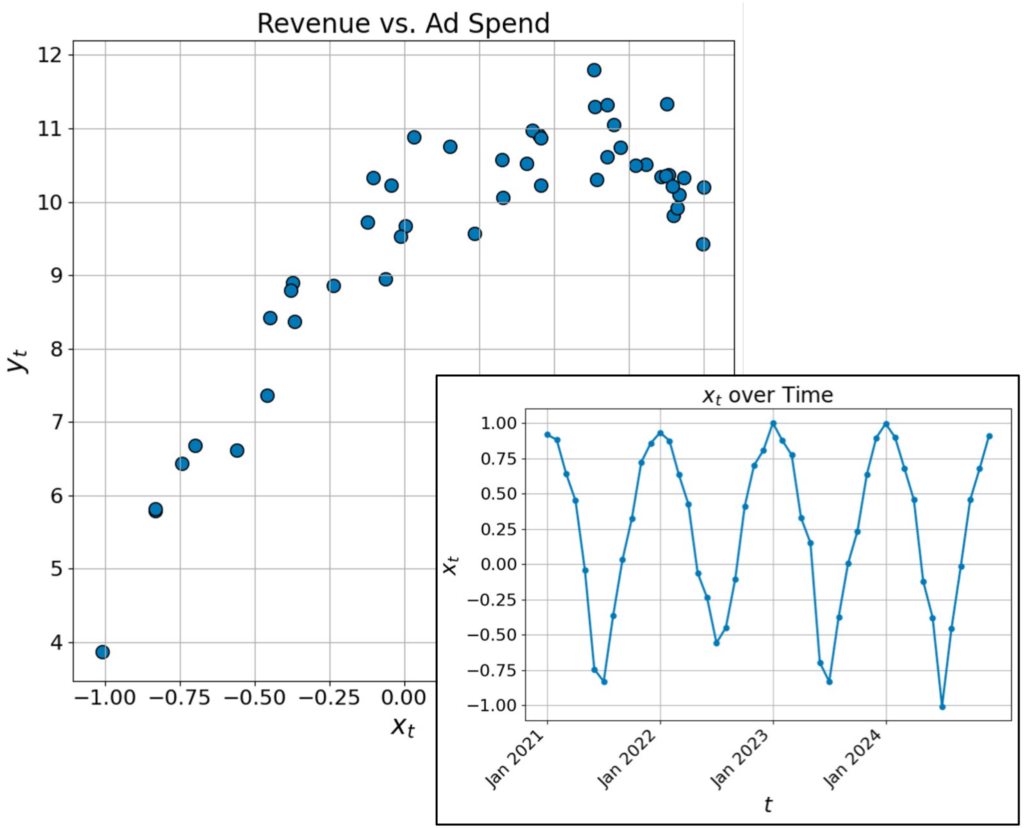

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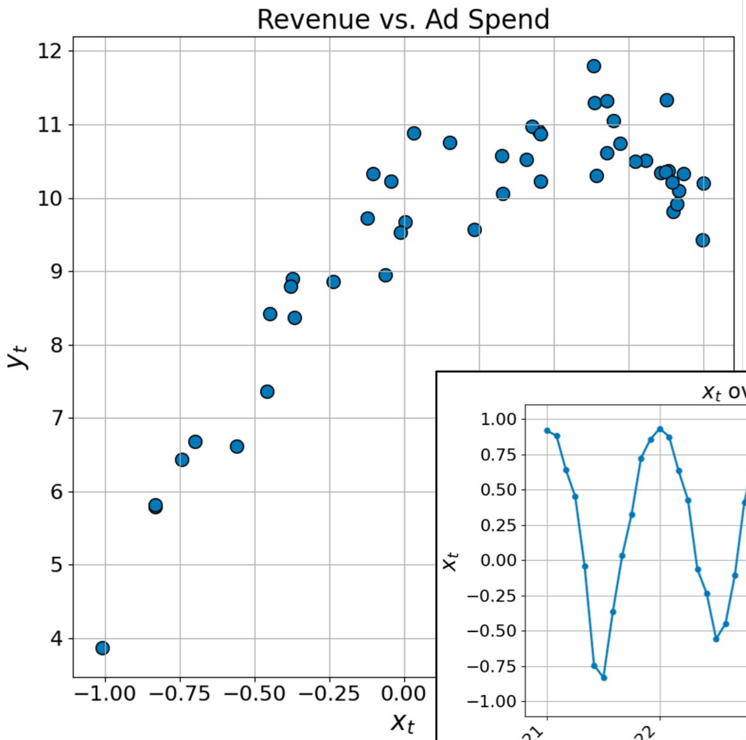

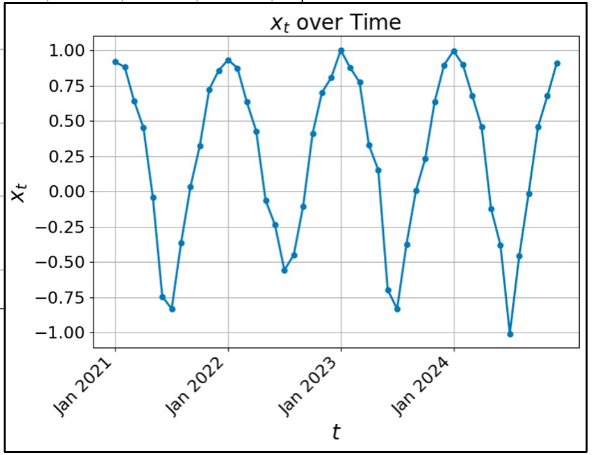

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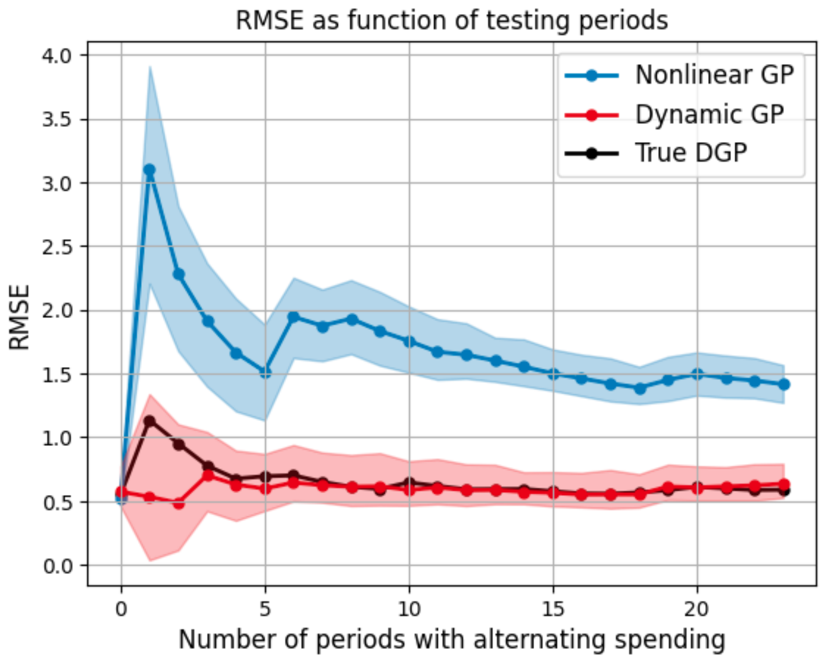

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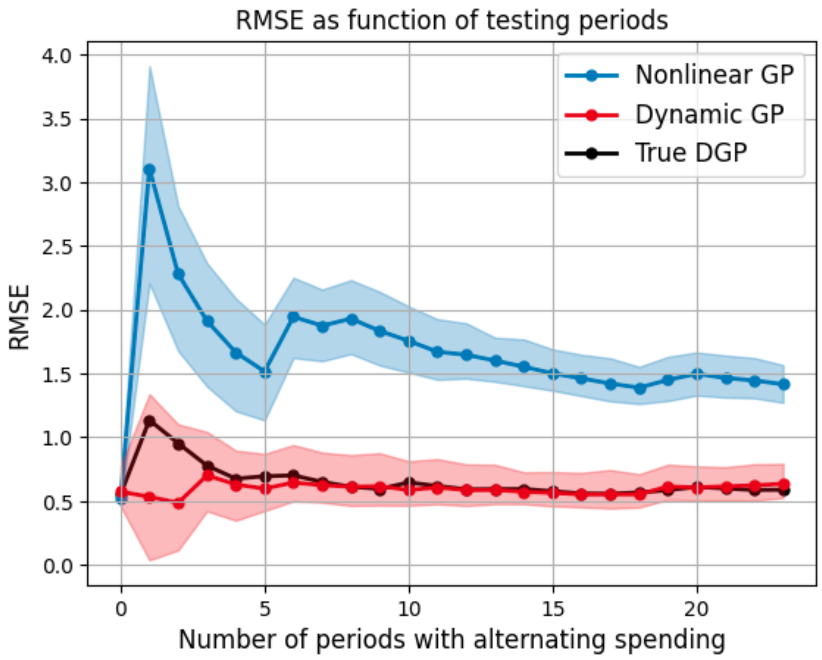
Ongoing work: optimal test design for model inference



Conclusions

Current MMM Practice Might Be Flawed!

- We show that, under many common spending patterns, **time-varying and nonlinear effects cannot be disentangled**, *despite having different implications*
- This problem is potentially **very widespread**: increasing complexity in models, widespread practice of “model refreshes” to capture changing markets
- Our work both introduces a **framework for estimating** these types of models, and provides **solutions for understanding and preventing** conflation

Thanks!

Feedback or questions:
ryandew@wharton.upenn.edu

Working paper soon:
www.rtdew.com

You
generate an image of a marketing mix model paradise with some very happy computers and a cameo from the reverend thomas bayes