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

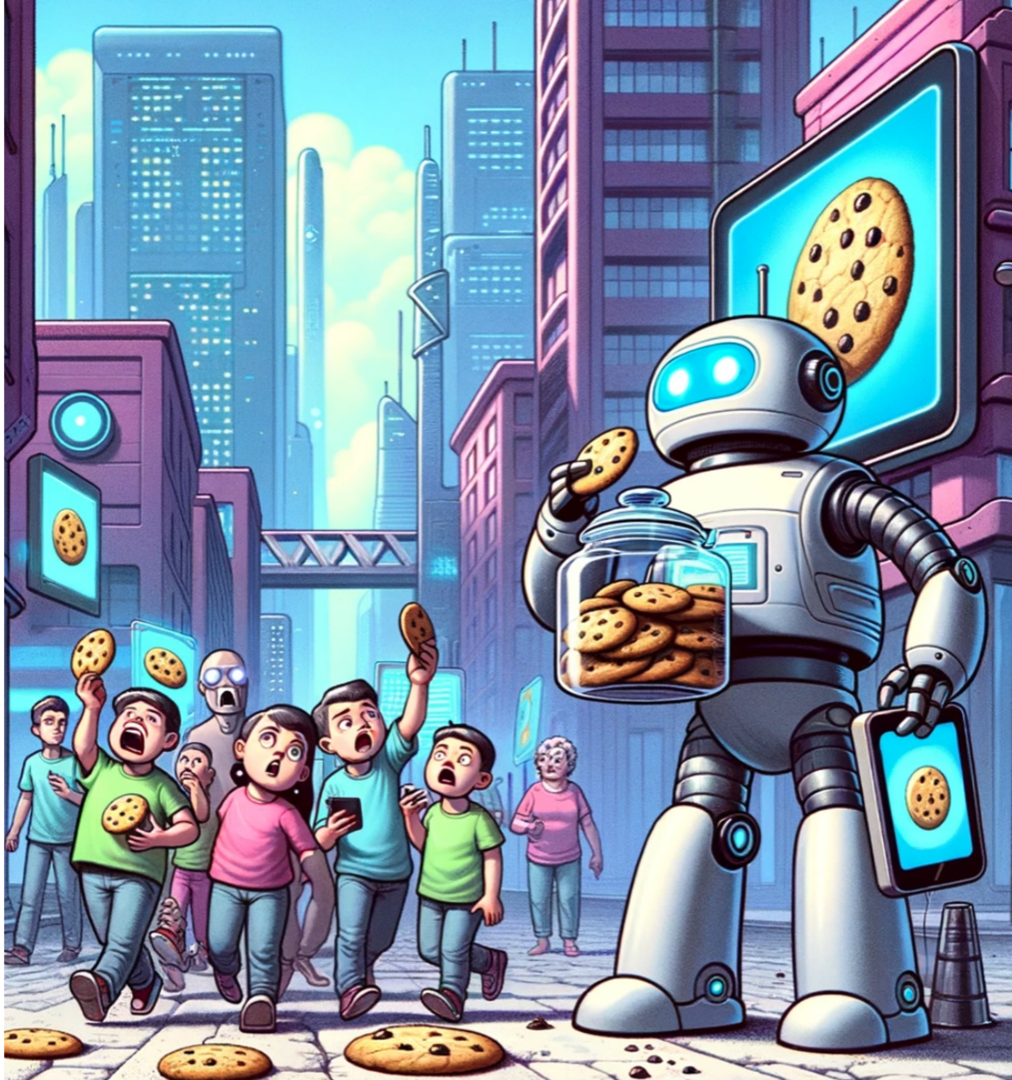
Ryan Dew

The Wharton School
University of Pennsylvania

Joint work with Nicolas Padilla and Anya Shchetkina

The Cookie-free Future

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



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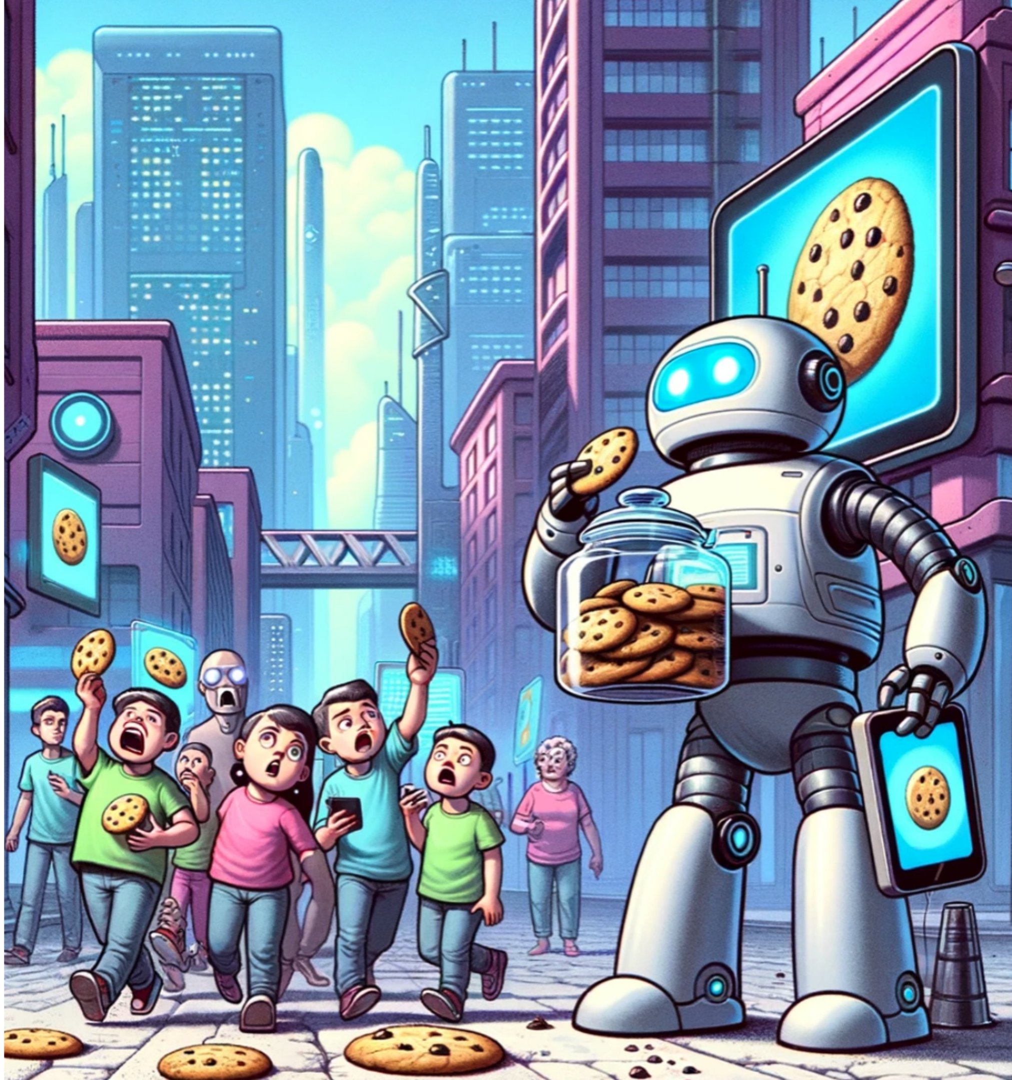

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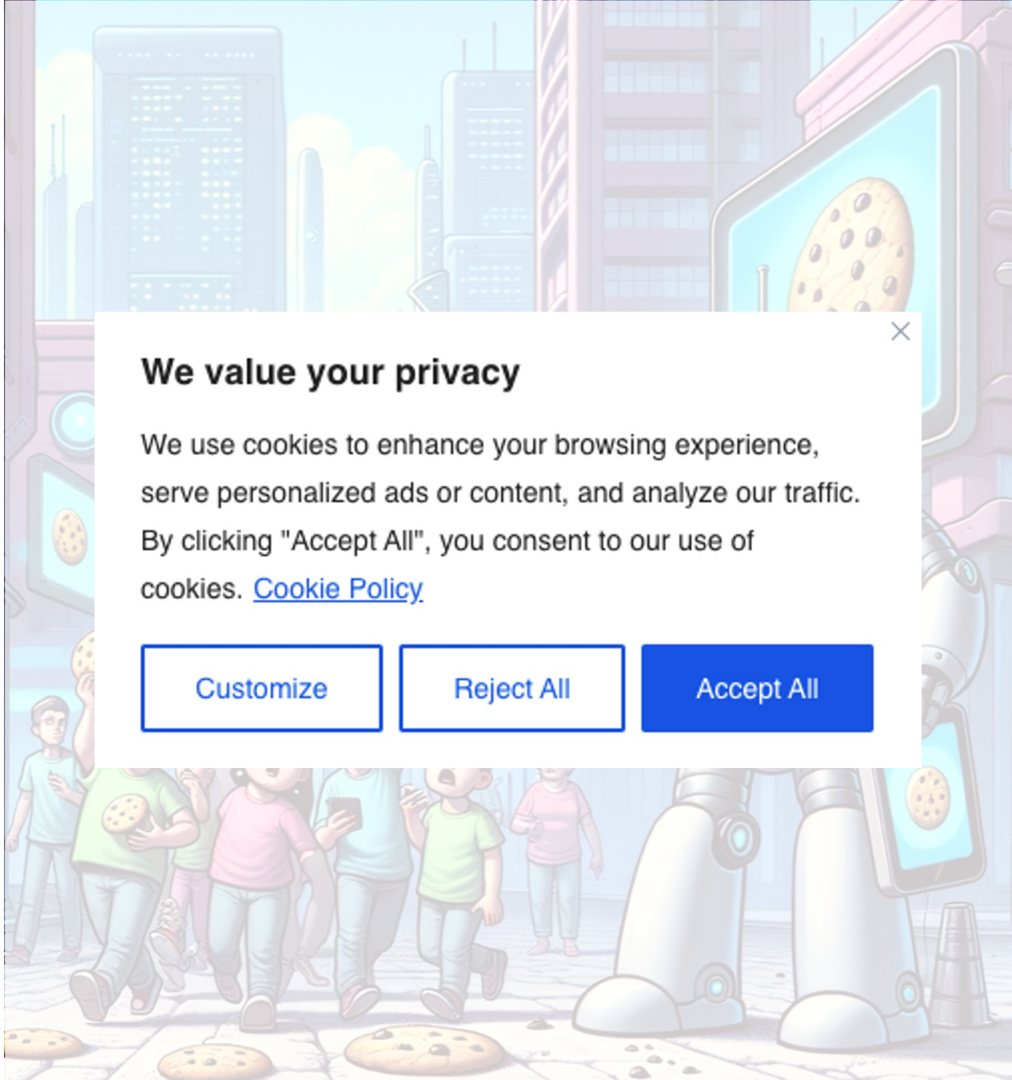

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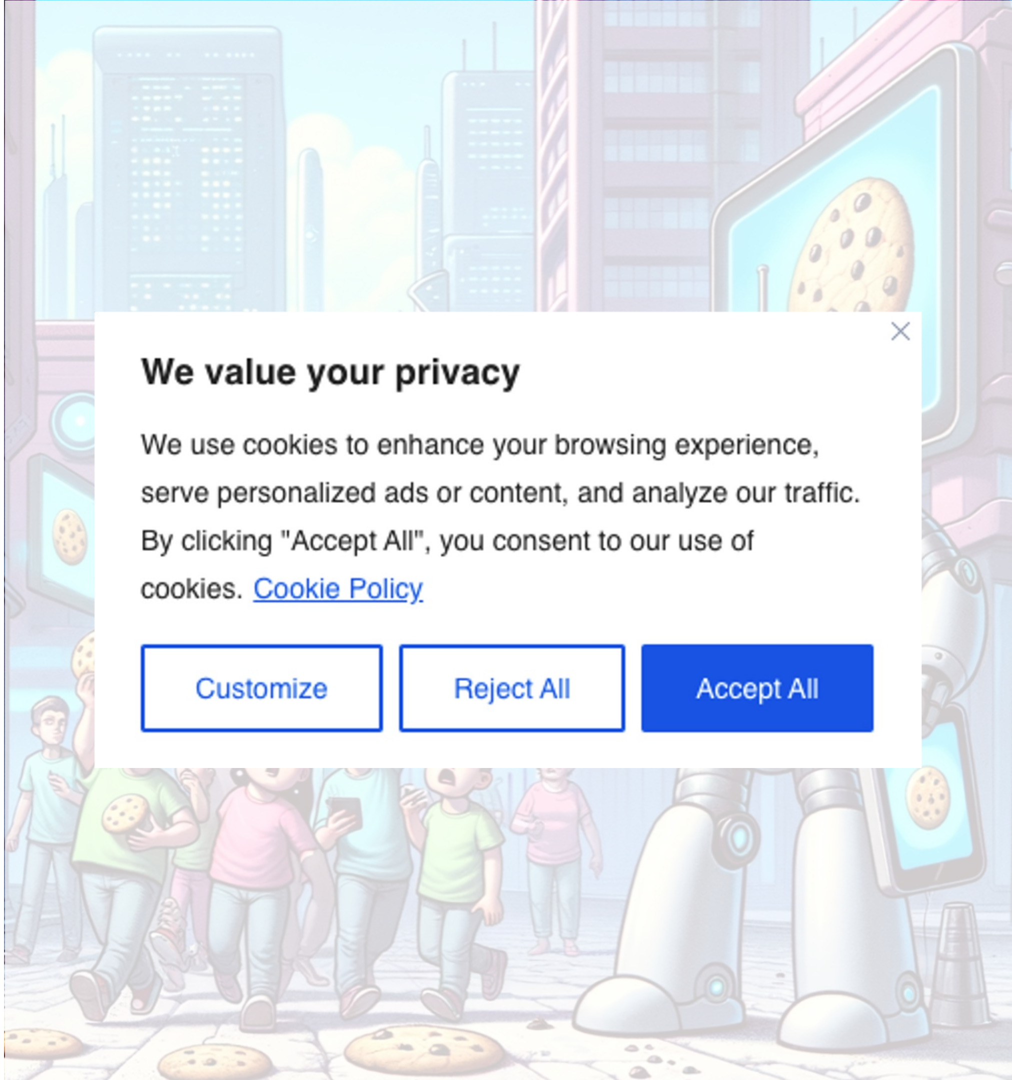
- Now? Gone!
- Result: huge resurgence in interest in models based on **aggregate data**




THE
RETURN
OF THE
MARKETING MIX MODEL
PRODUCT
PLACE
PLACE
PROMOTION

[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.

arXiv > stat > arXiv:2106.03322

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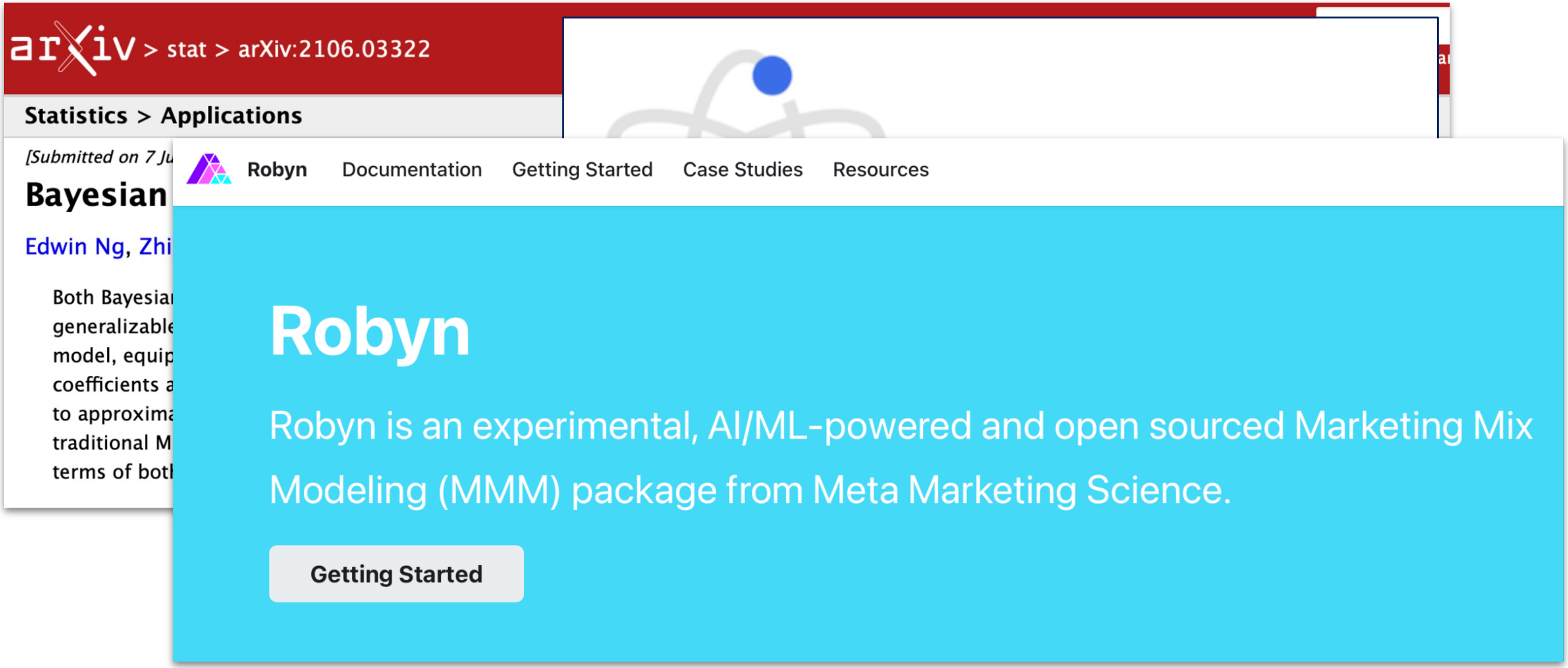
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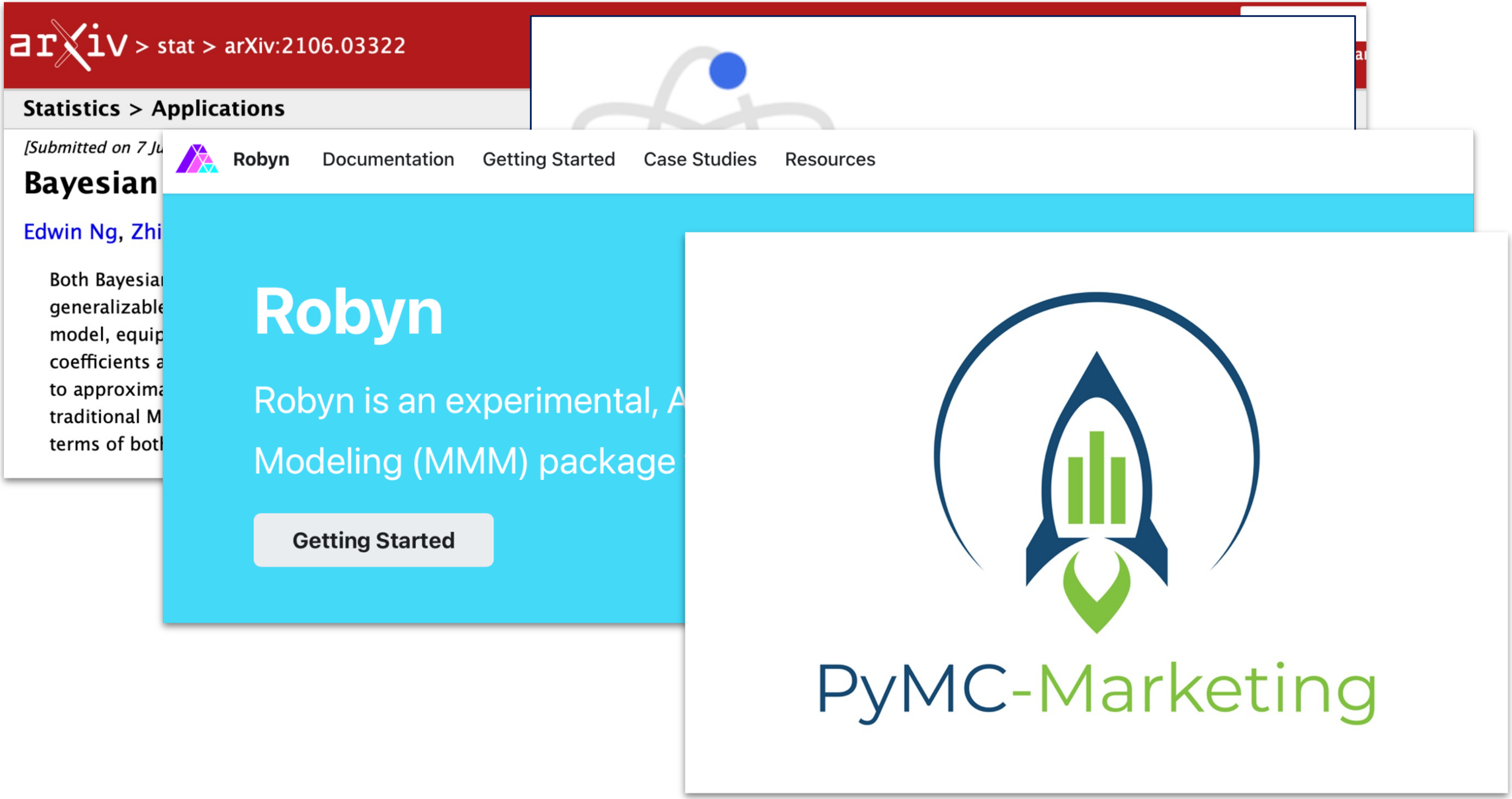
Getting Started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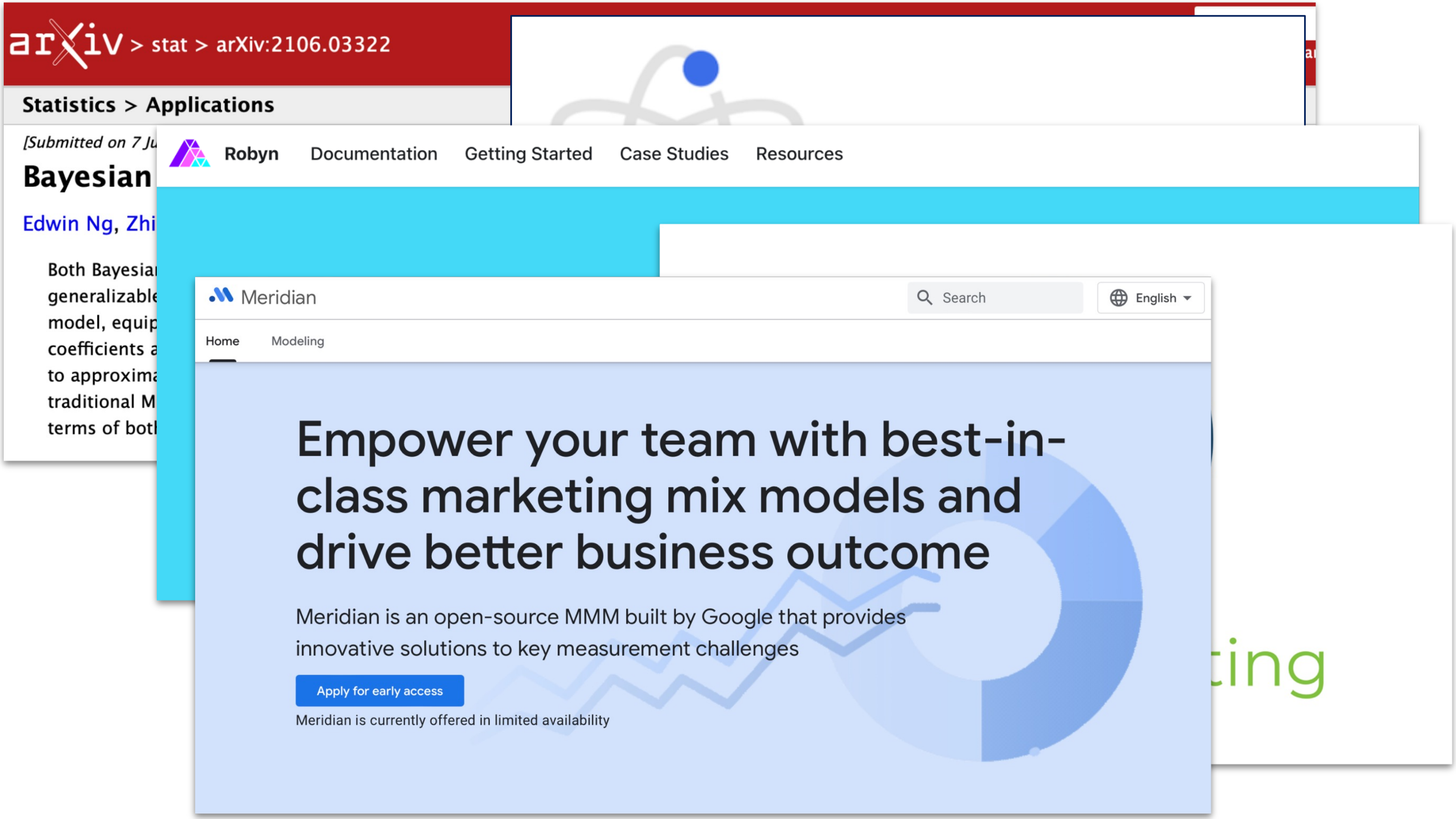
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Meridian
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Modeling
Empower your team with best-in-class marketing mix models and drive better business outcome
Meridian is an open-source MMM built by Google that provides innovative solutions to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

- Very long history in marketing
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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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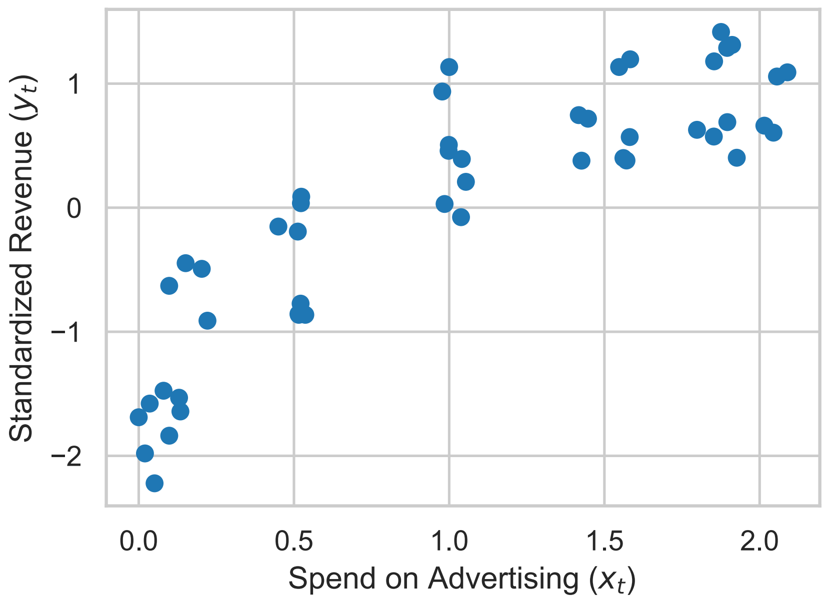
Uber's Orbit

Ng et al., (2021)

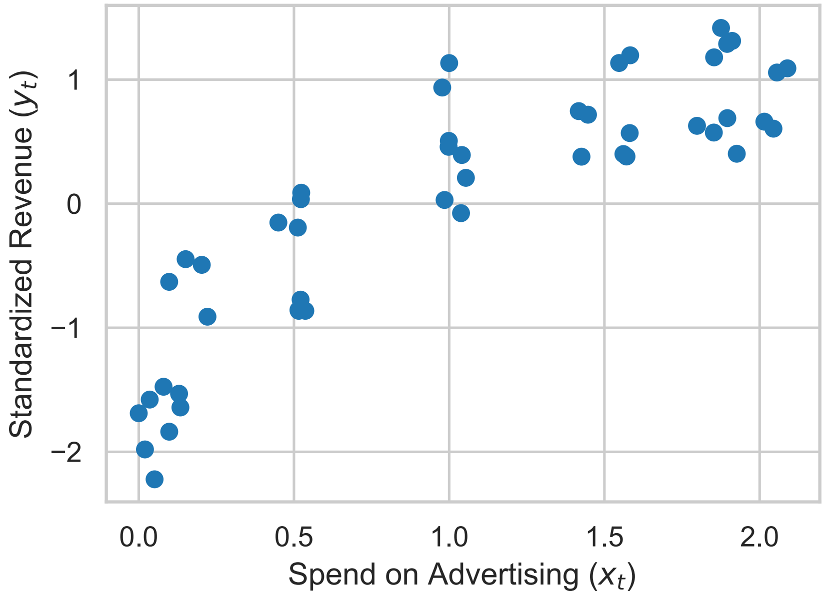
$$ln(\hat{y}_t) = l_t + s_t + \sum_{p=1}^{P} ln(x_{t,p})\beta_{t,p}$$

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

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



Standardized Revenue (y_t)
1
0
−1
−2
0.0
0.5
1.0
1.5
2.0
Spend on Advertising (x_t)



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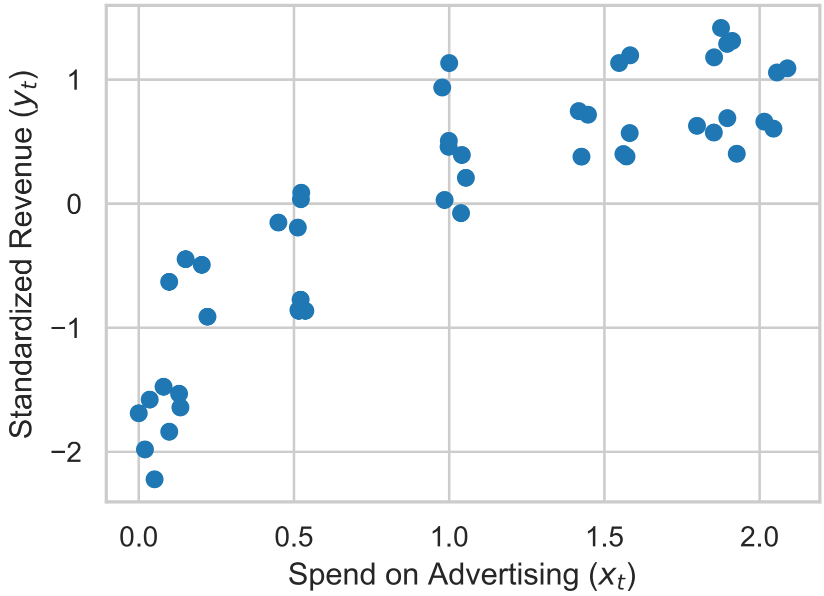

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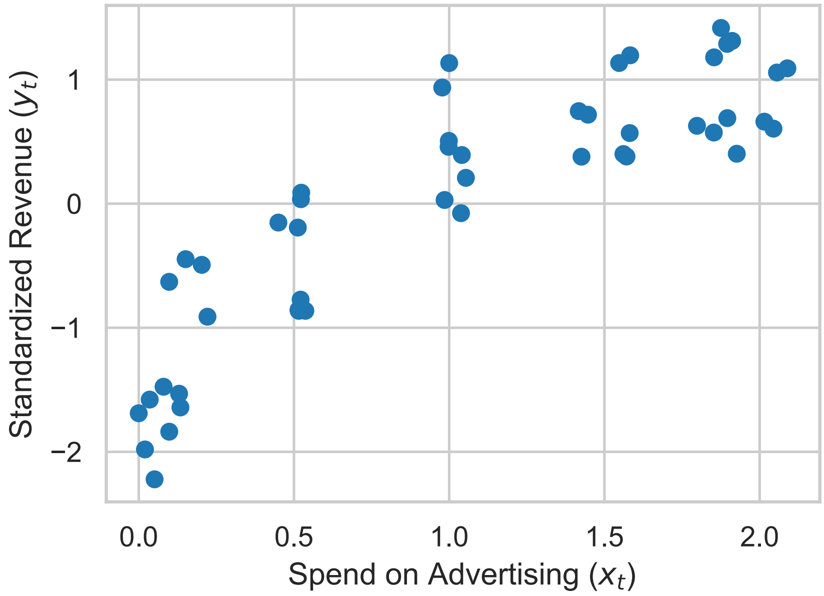

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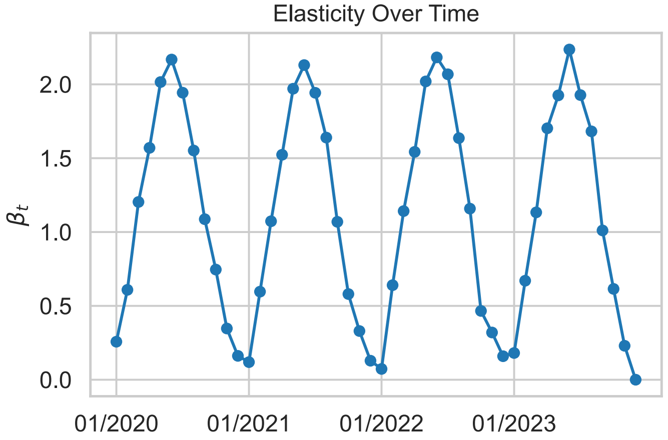

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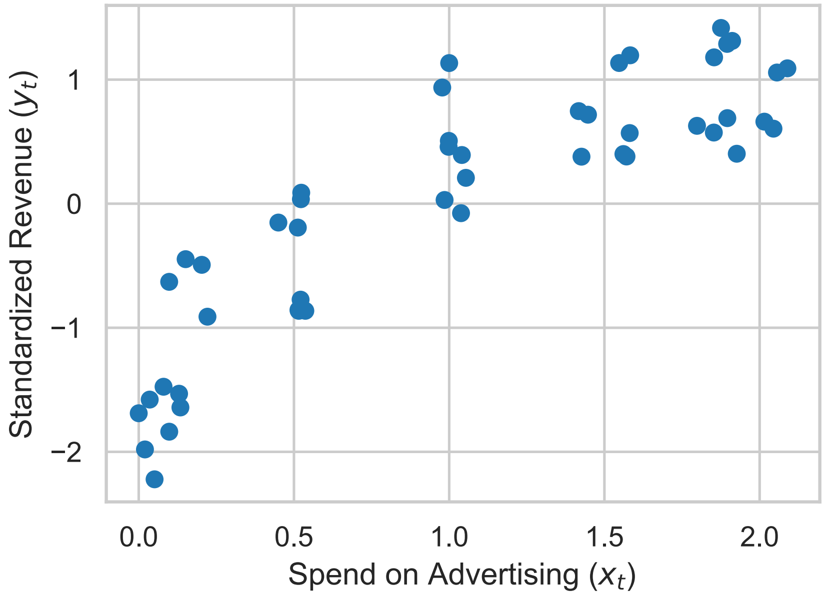

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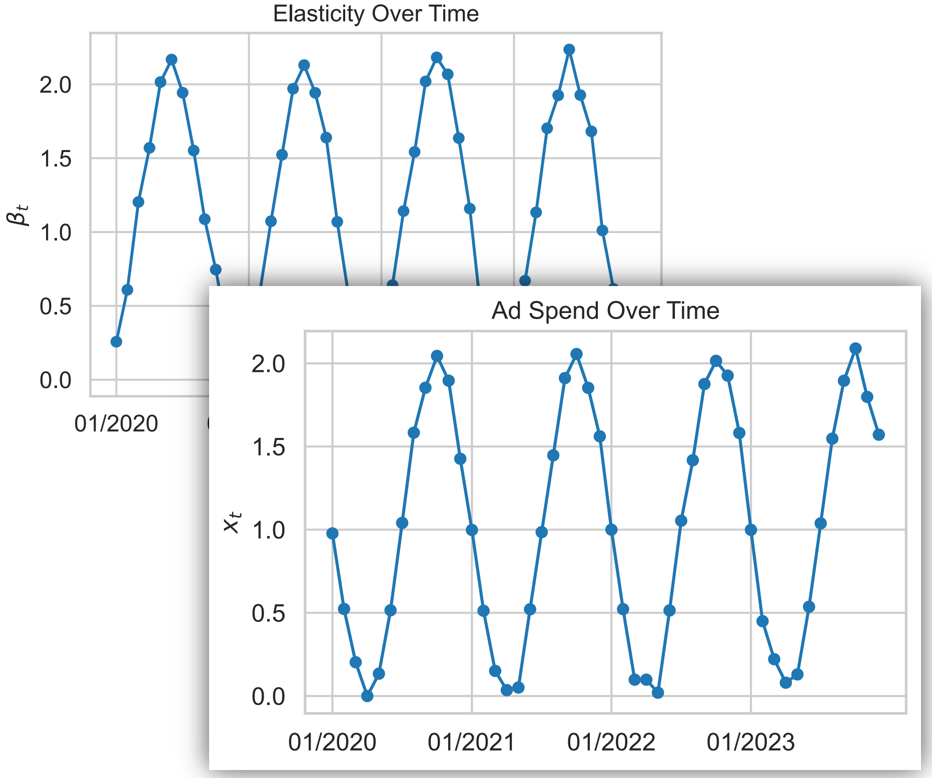

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3. Problems are exacerbated under common managerial practices, like **autoregressive decision-making**
4. Similarly fitting models can have **fundamentally different implications** in terms of optimal decision-making

(A little) Math

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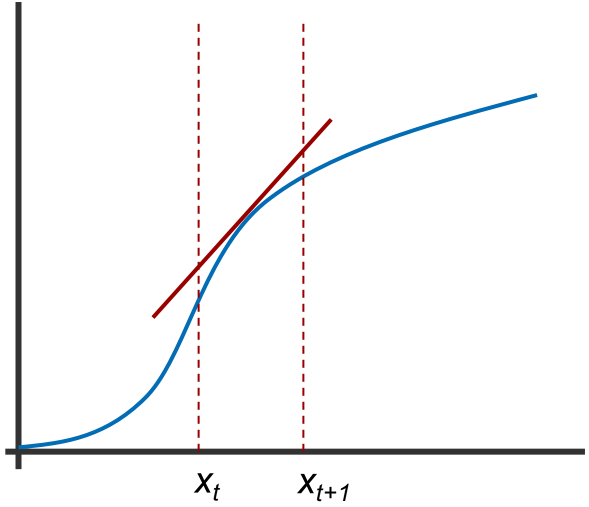

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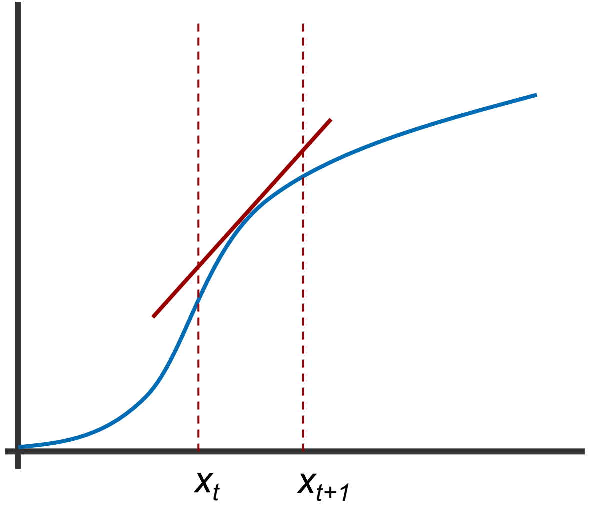
- When will β_t be smooth ("forecastable")? If f is smooth and x_t and x_{t+1} are close together!



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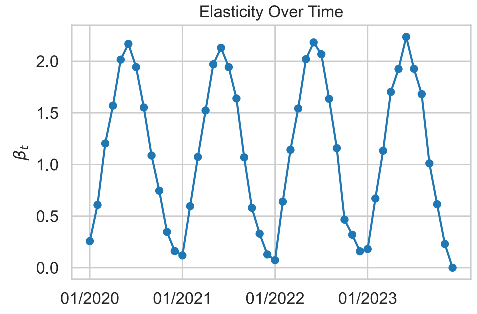

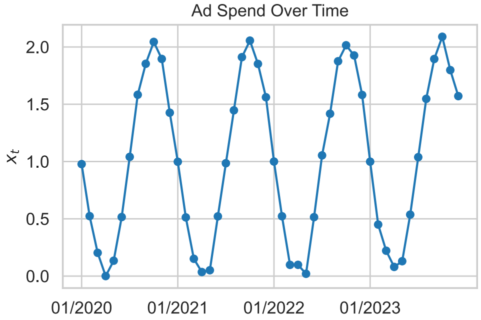

Simulations

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

$$y_t = \beta(t)x_t + \varepsilon_t$$

3. Nonlinear response, parametric hill function

$$y_t = \mathrm{Hill}(x_t) + \varepsilon_t$$

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

$$\upharpoonleft\downharpoonright$$

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

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

Primer: Gaussian Processes

Gaussian processes: a Bayesian nonparametric approach to modeling unknown functions

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

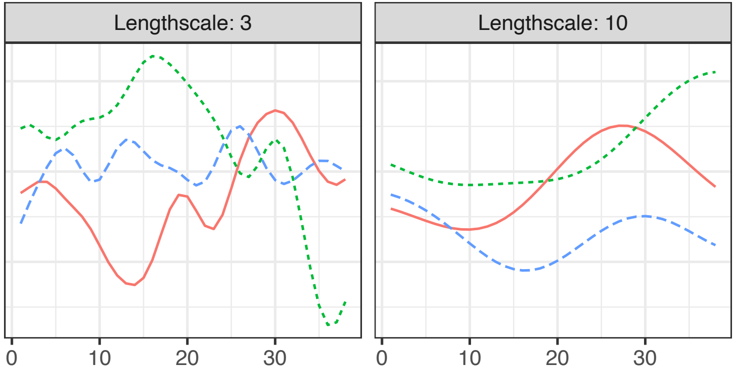
$$\uparrow\downarrow$$

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

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

When does conflation *actually* happen?

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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

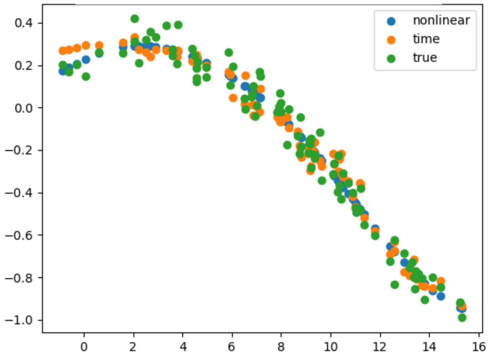
- For each simulation type, >300 settings, systematically varying the previously described factors, with 100 simulations per setting
- Fit both models (nonlinear and dynamic), measure conflation through validation RMSE

Examples

Nonlinear DGP

Smooth f, low noise

Data

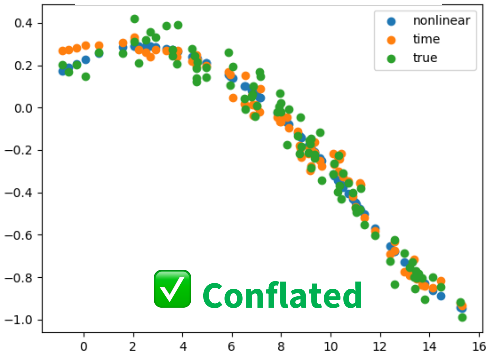


Examples

Nonlinear DGP

Smooth f, low noise

Data

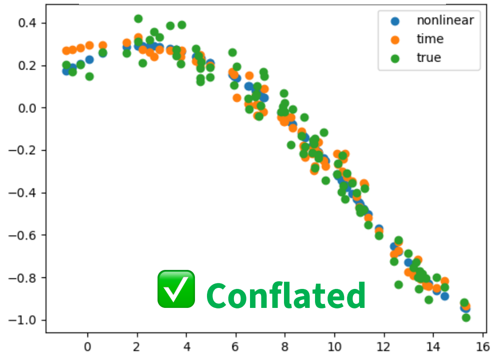


Examples

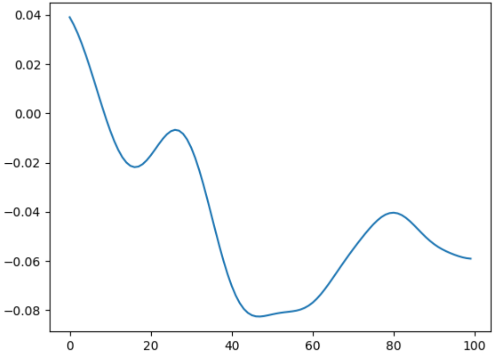
Nonlinear DGP

Smooth f, low noise

Data



Implied $\beta(t)$



Examples

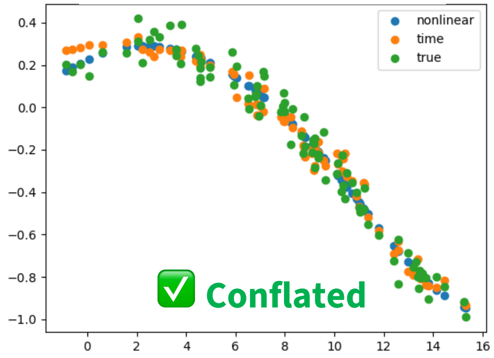
Nonlinear DGP

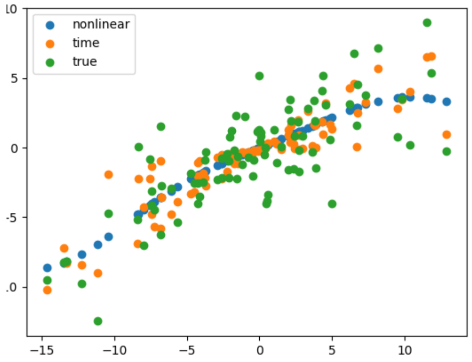
Smooth f, low noise

Dynamic DGP

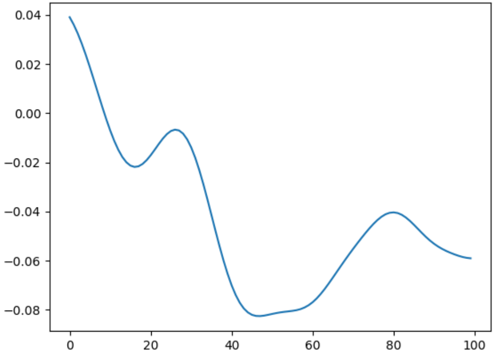
Smooth f, low noise

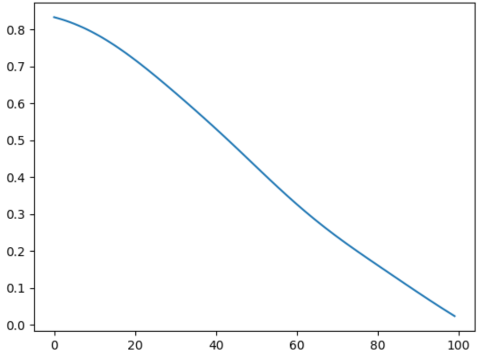
Data





Implied $\beta(t)$





Examples

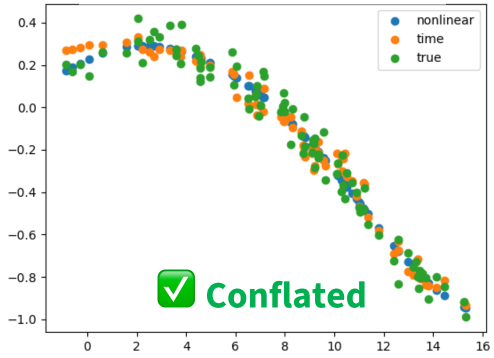
Nonlinear DGP

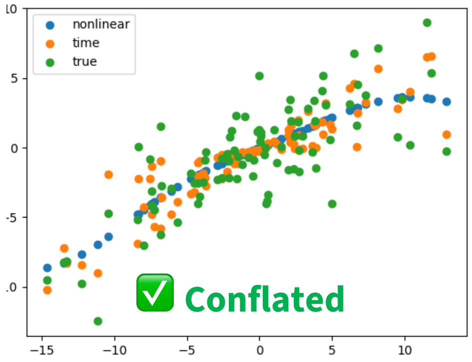
Smooth f, low noise

Dynamic DGP

Smooth f, low noise

Data





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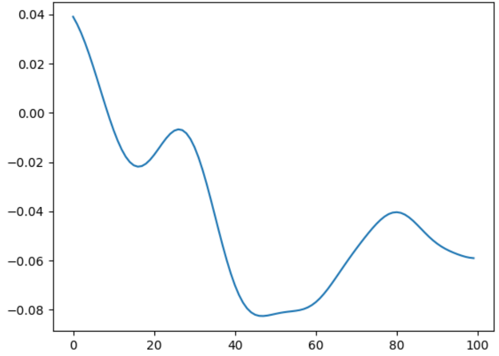
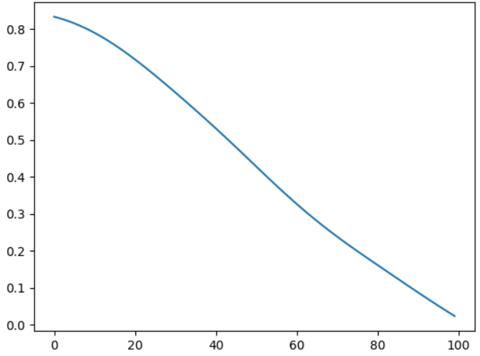




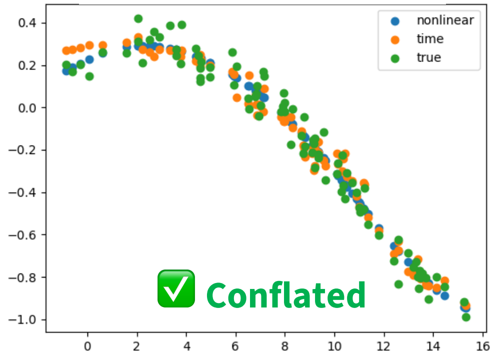
Examples

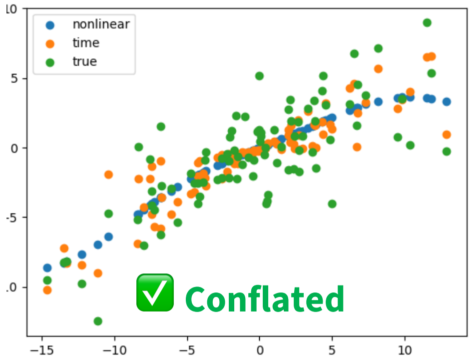
Nonlinear DGP
Smooth f, low noise

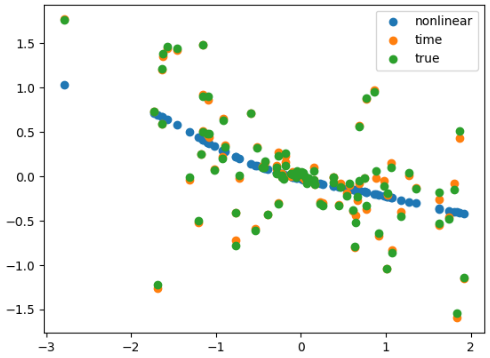
Dynamic DGP
Smooth f, low noise

Dynamic DGP
Less smooth f, low noise

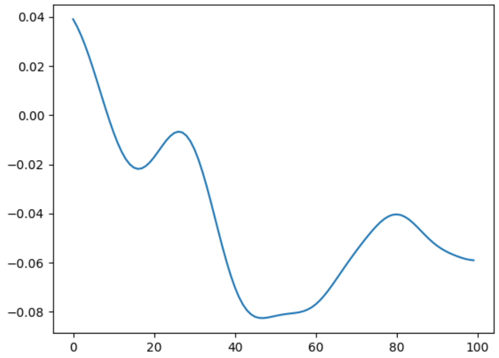
Data

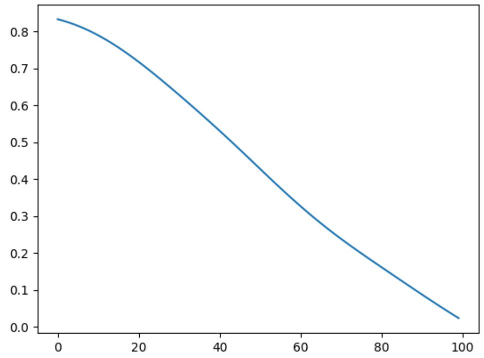


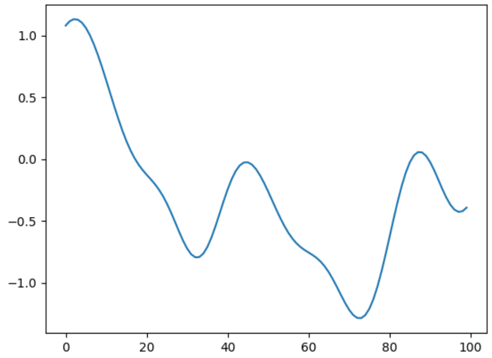




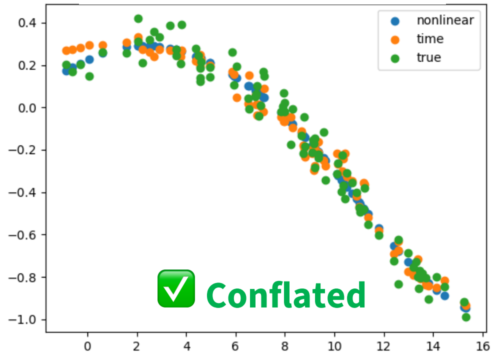
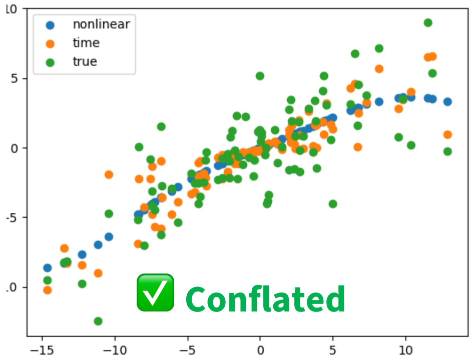
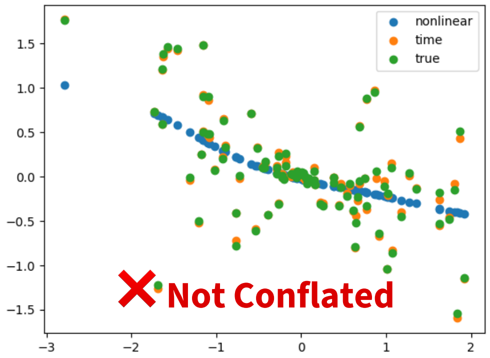
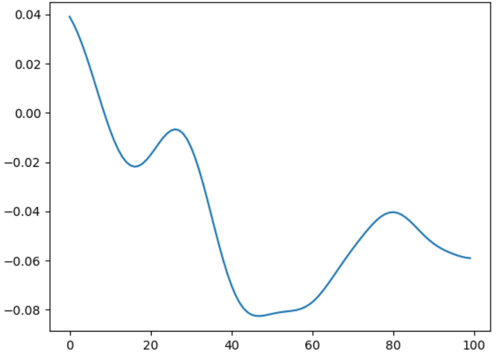
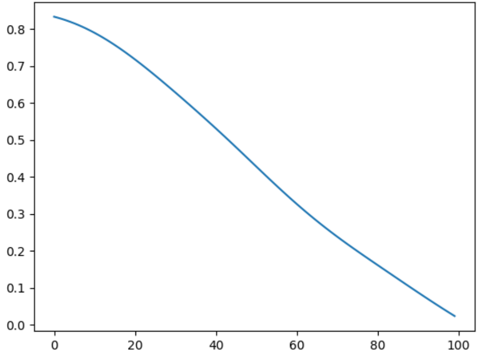
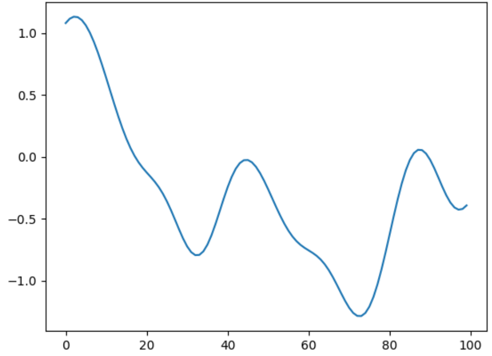
Implied $\beta(t)$







Examples

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

Simulation Results

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

Simulation Results

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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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Diving Deeper

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Conflation more likely with…

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Decisions are often autocorrelated!

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

Even worse with AdStock

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

with **37% exhibiting major conflation**

(previously: 82% and 23%)

Even worse with AdStock

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

with **37% exhibiting major conflation**

(previously: 82% and 23%)

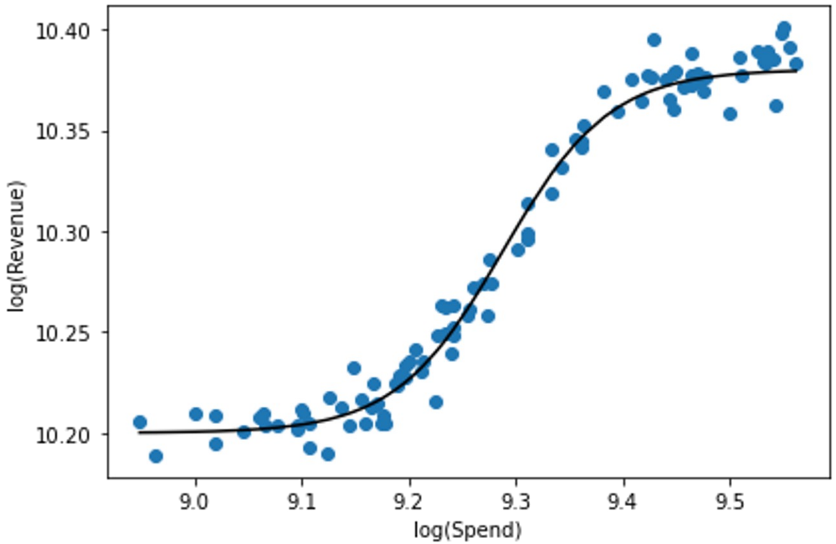
Under the time-varying DGP with AdStock, **87%** exhibited some conflation,

with **52% exhibiting major conflation**

(previously: 80% and 27%)

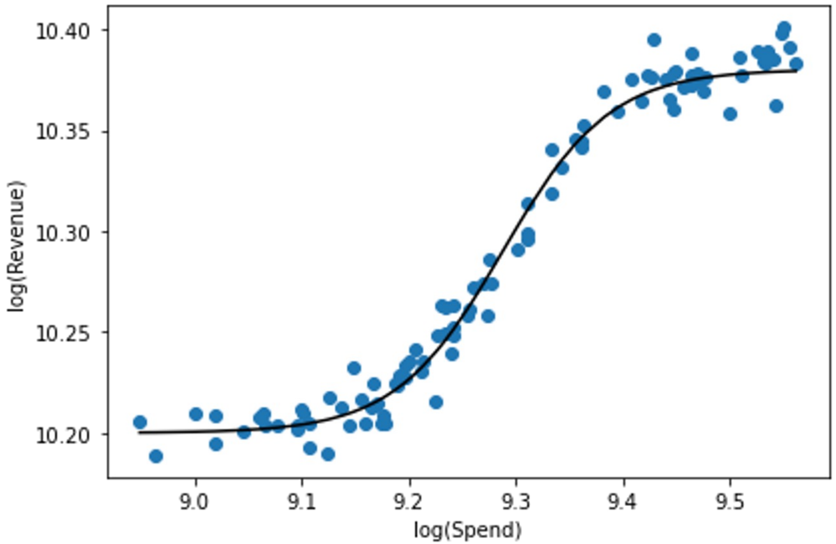
Implications

One last simulation…



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

One last simulation…



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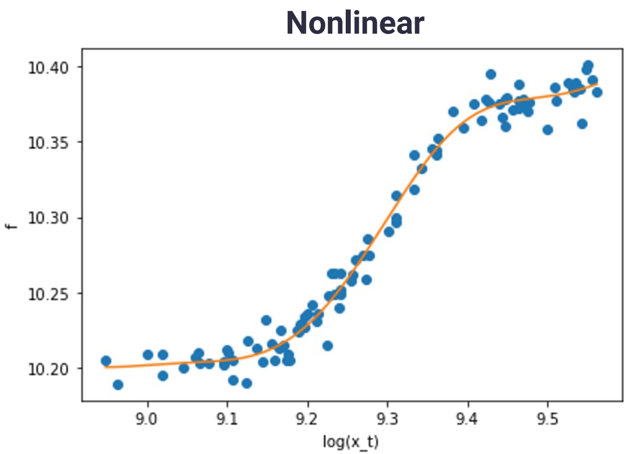

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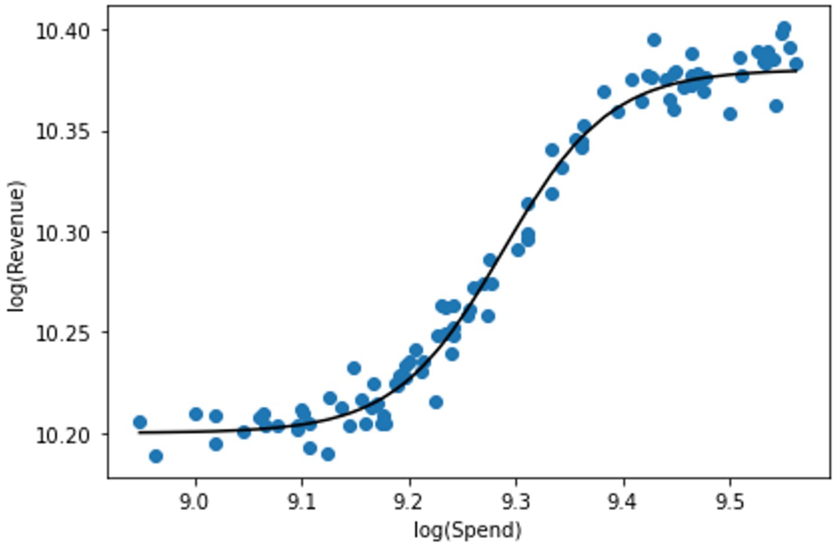

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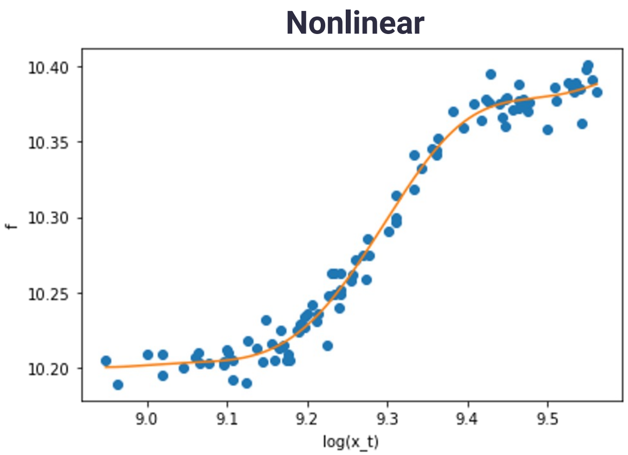

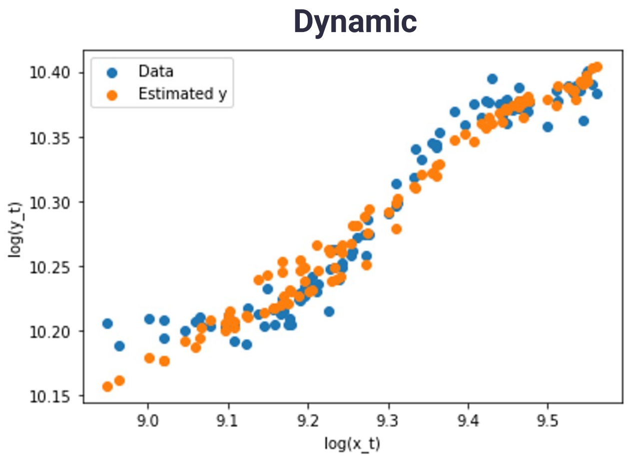

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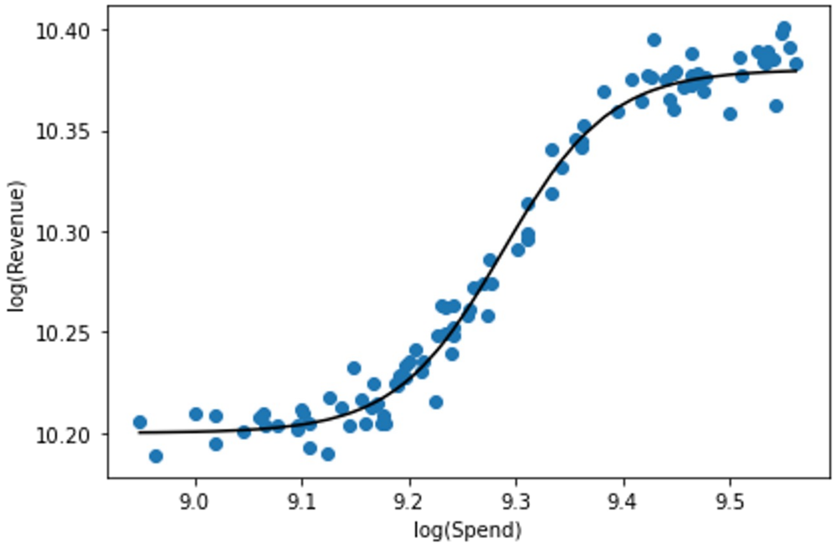

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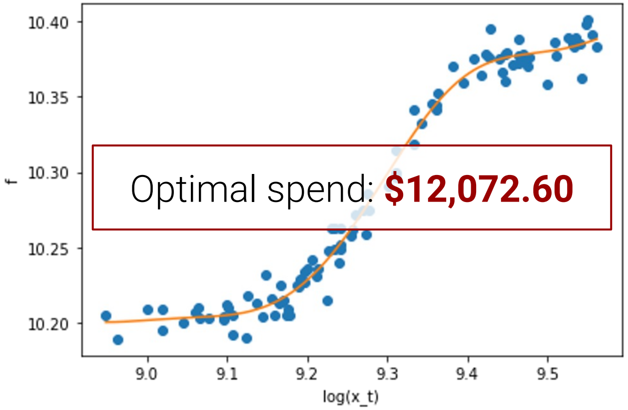
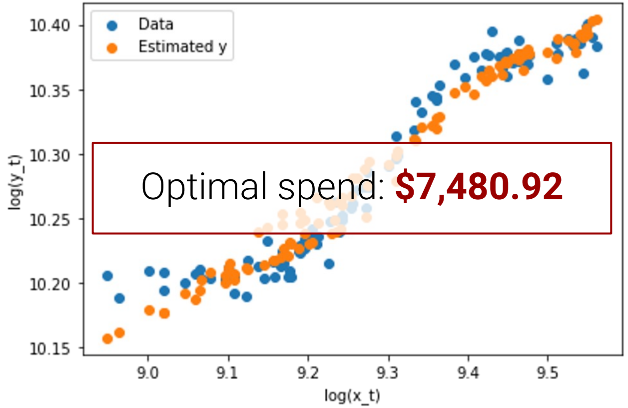
Nonlinear



Dynamic



Real Data: Classic and Modern

- Classic Application 1: Dietary Weight Control (DWC)
  (Bass and Clark, 1972)

- Classic Application 2: Lydia Pinkham (LP)
  (Palda, 1964)

- Modern Applications: MMM data constructed from Nielsen

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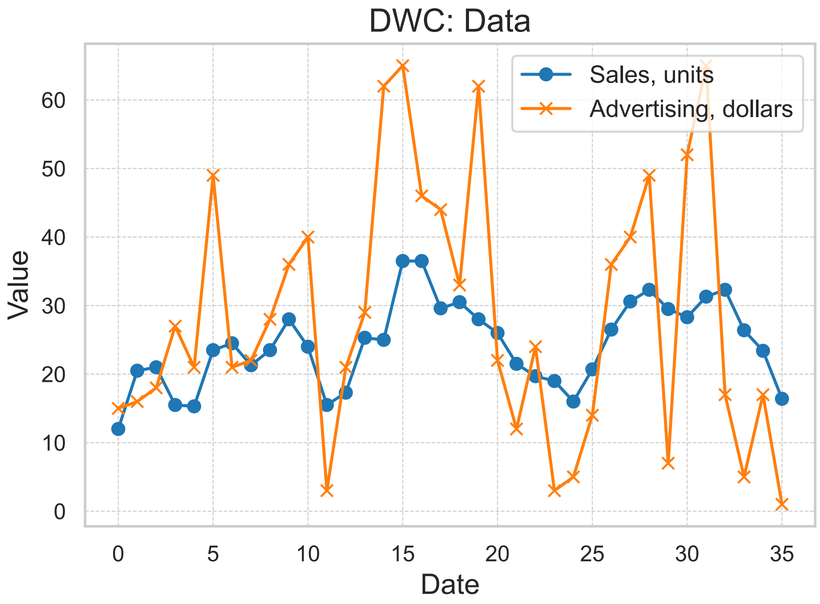
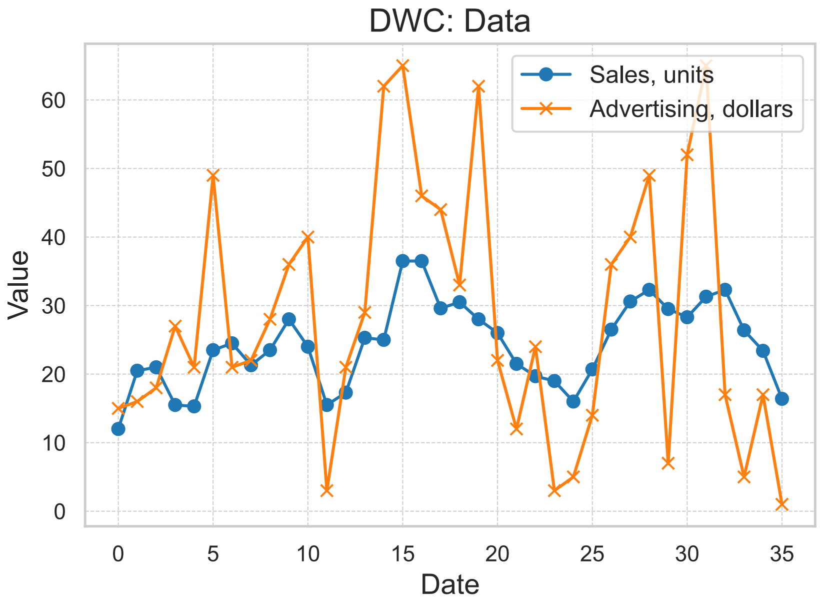
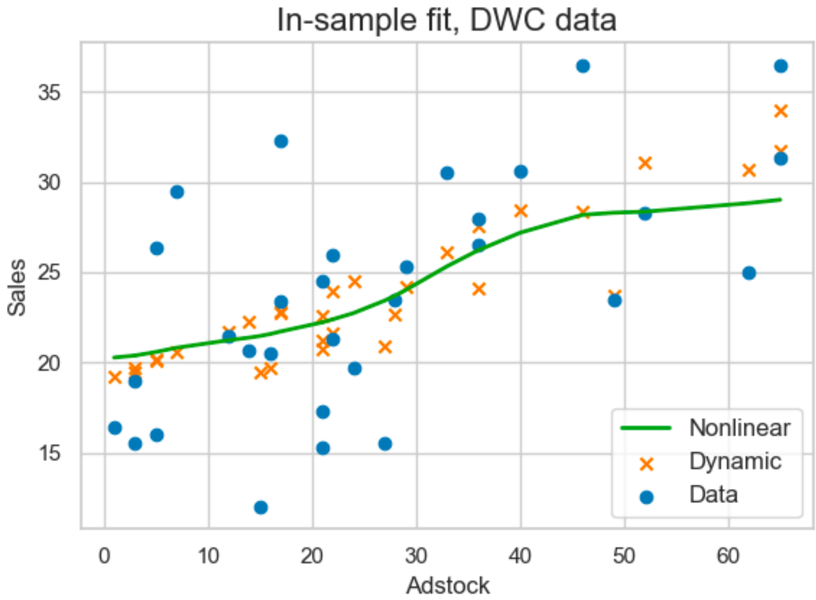
Dietary Weight Control



Dietary Weight Control





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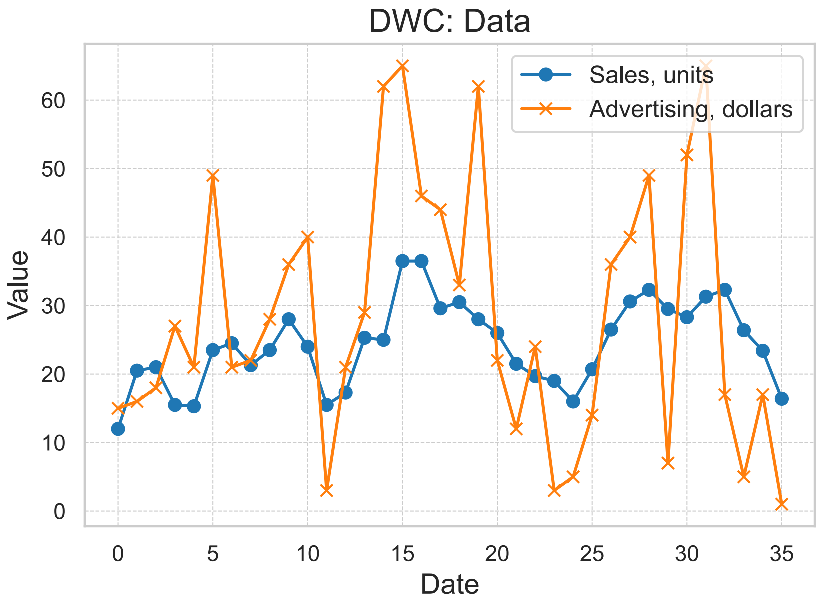
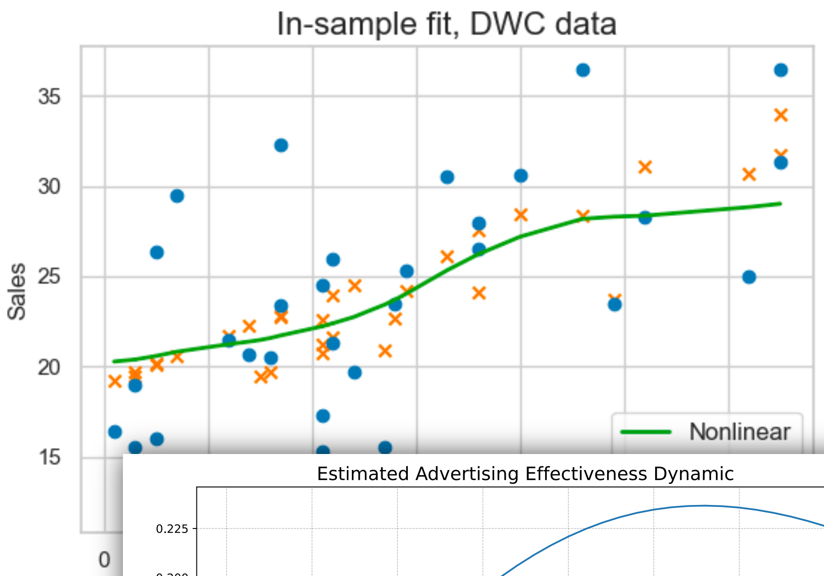
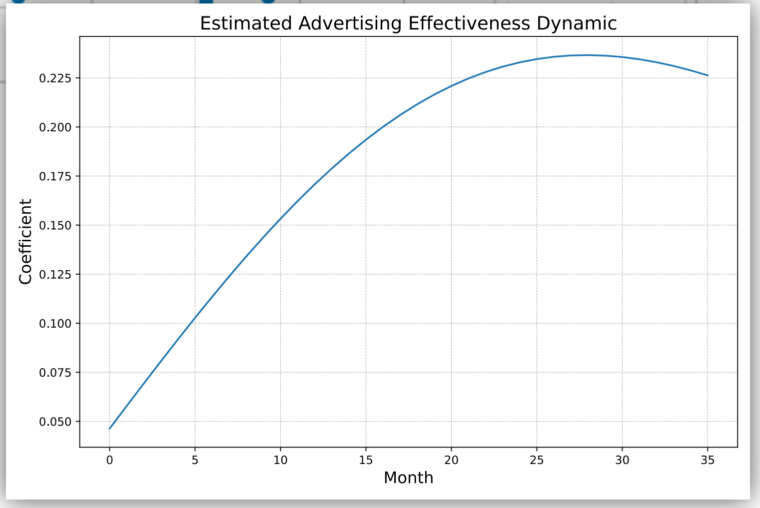
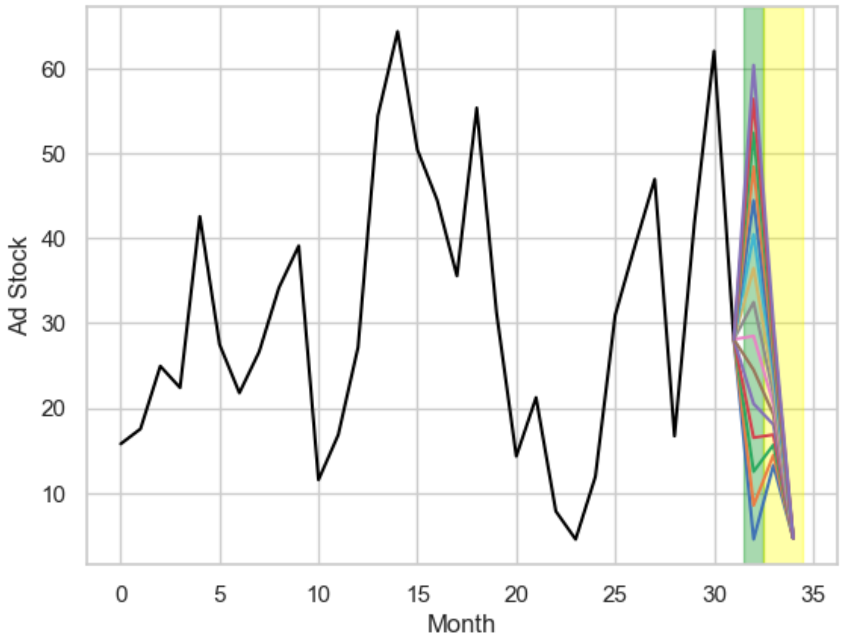






Ad Optimization a la Google



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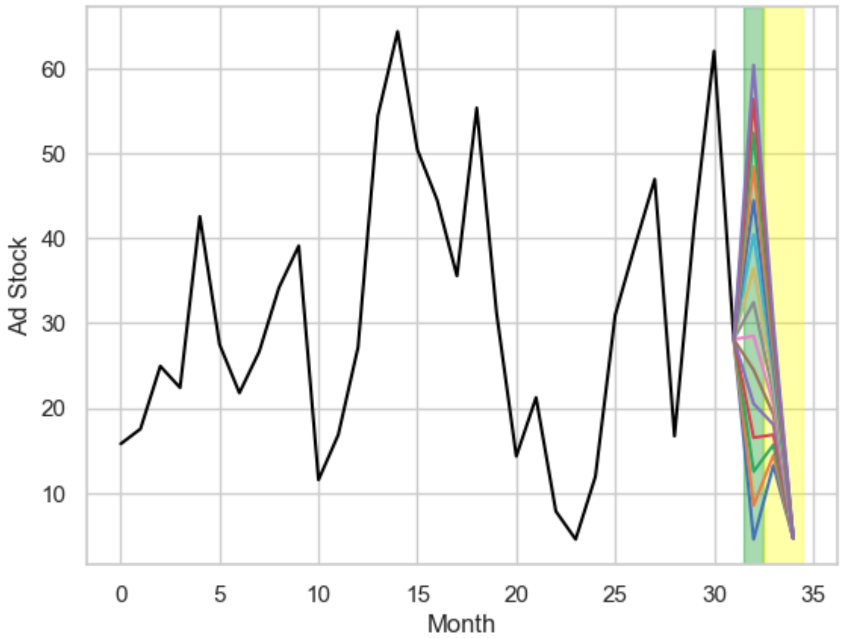
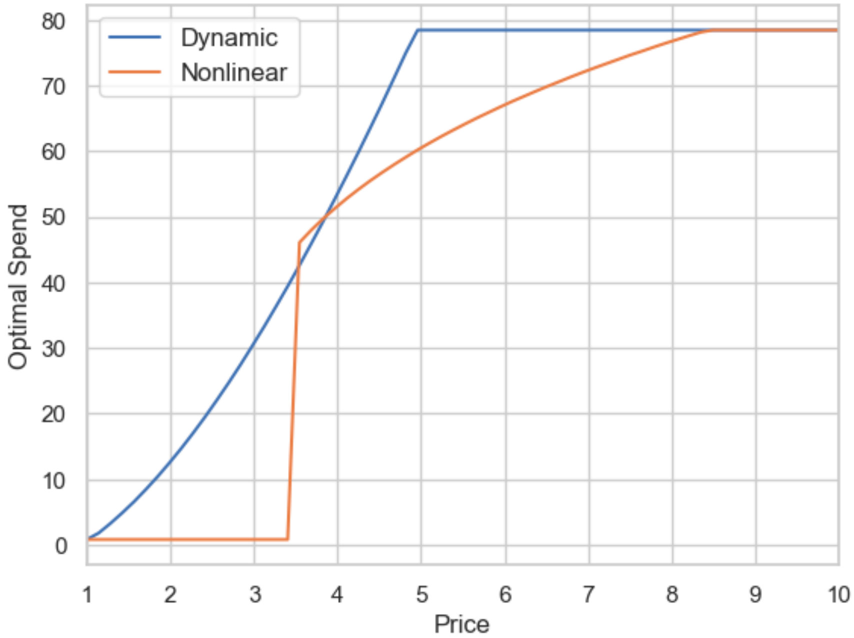
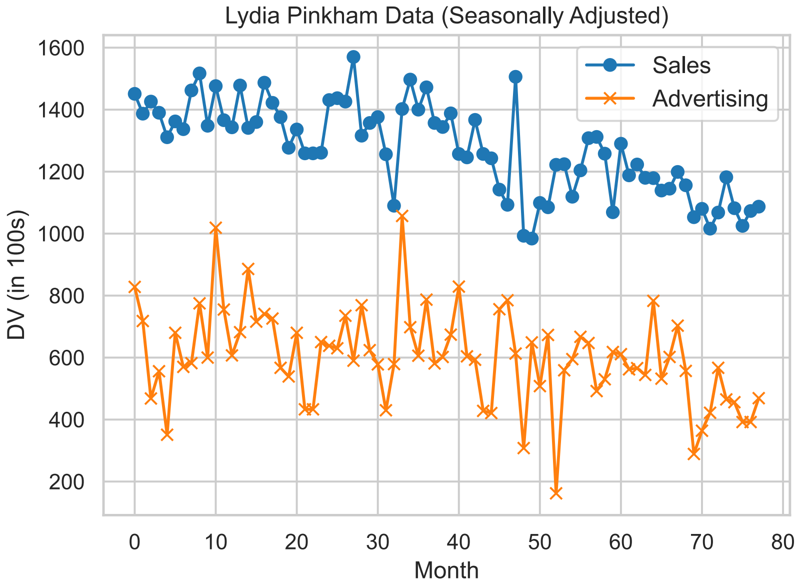




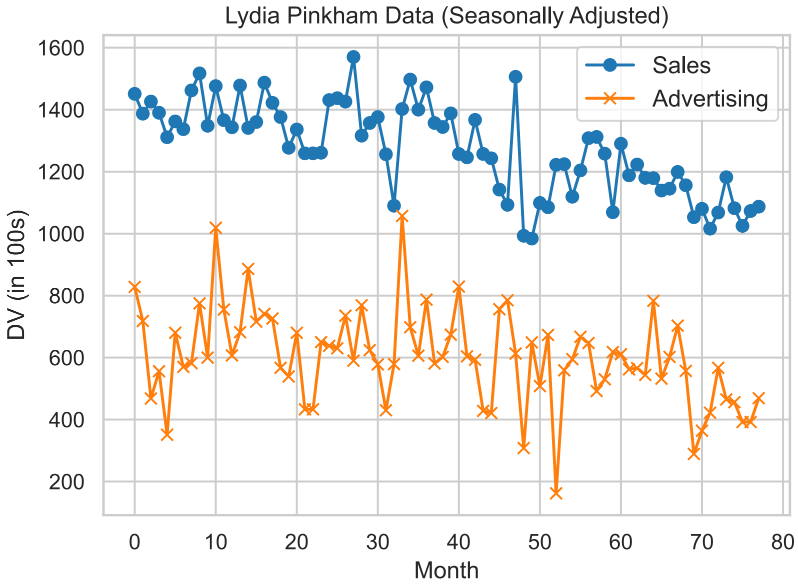
Lydia Pinkham

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



Lydia Pinkham

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



Lydia Pinkham

150 Tablets

764

50+ bought in past month

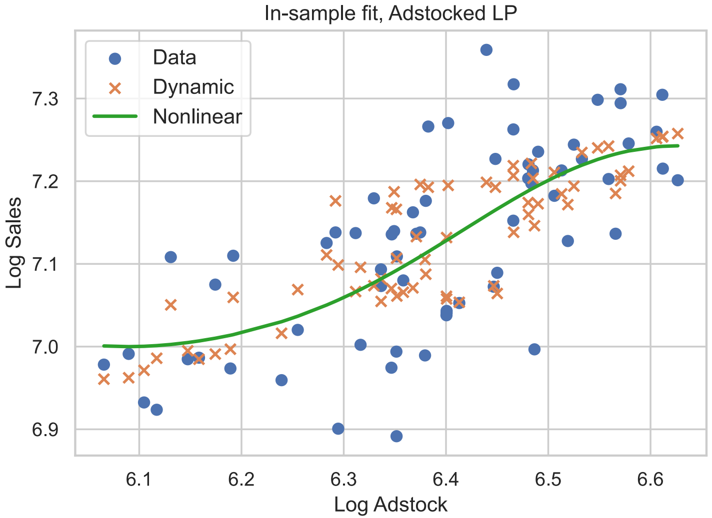
$21.99 ($0.15/Count)

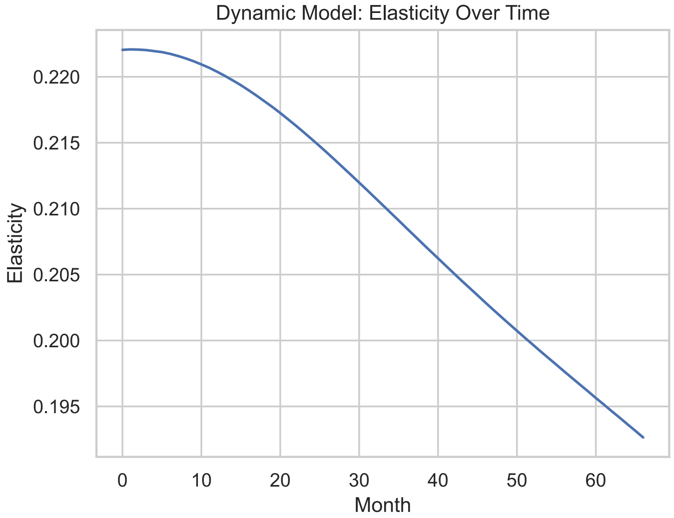
prime Two-Day

FREE delivery **Thu, May 9**

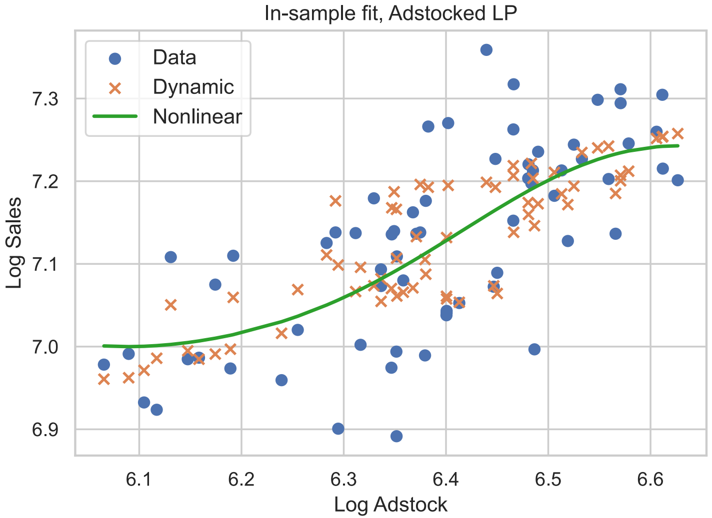
Add to cart

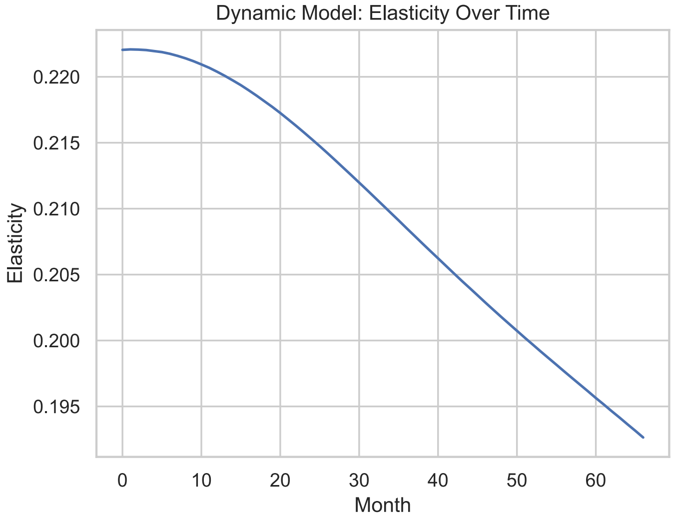
Again, conflated...





Again, conflated...





and yield different optimal expenditures.

Under nonlinear: **$89,883**

Under dynamic: < $**78,333**

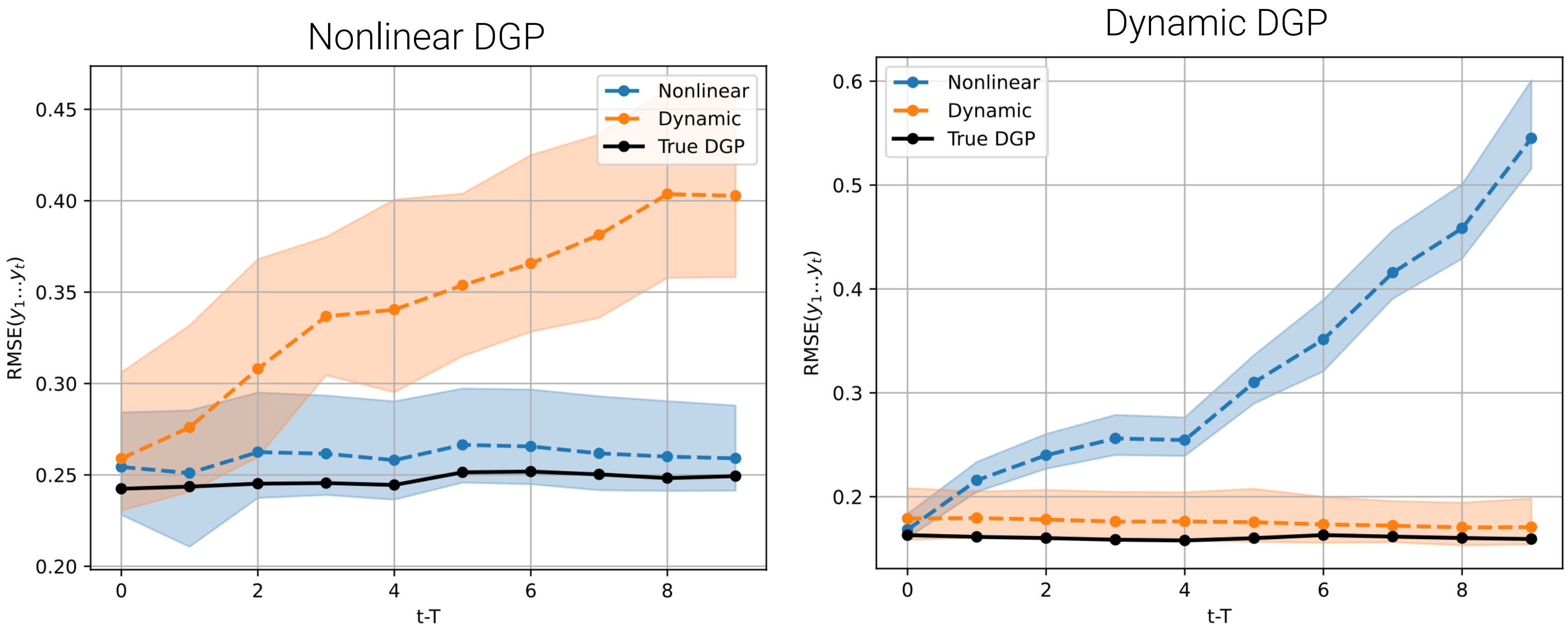
Solutions

Is MMM doomed?

- In short: **no!**
- Careful ad planning can help disentangle the two stories
- **“Bump-up” incrementality tests**

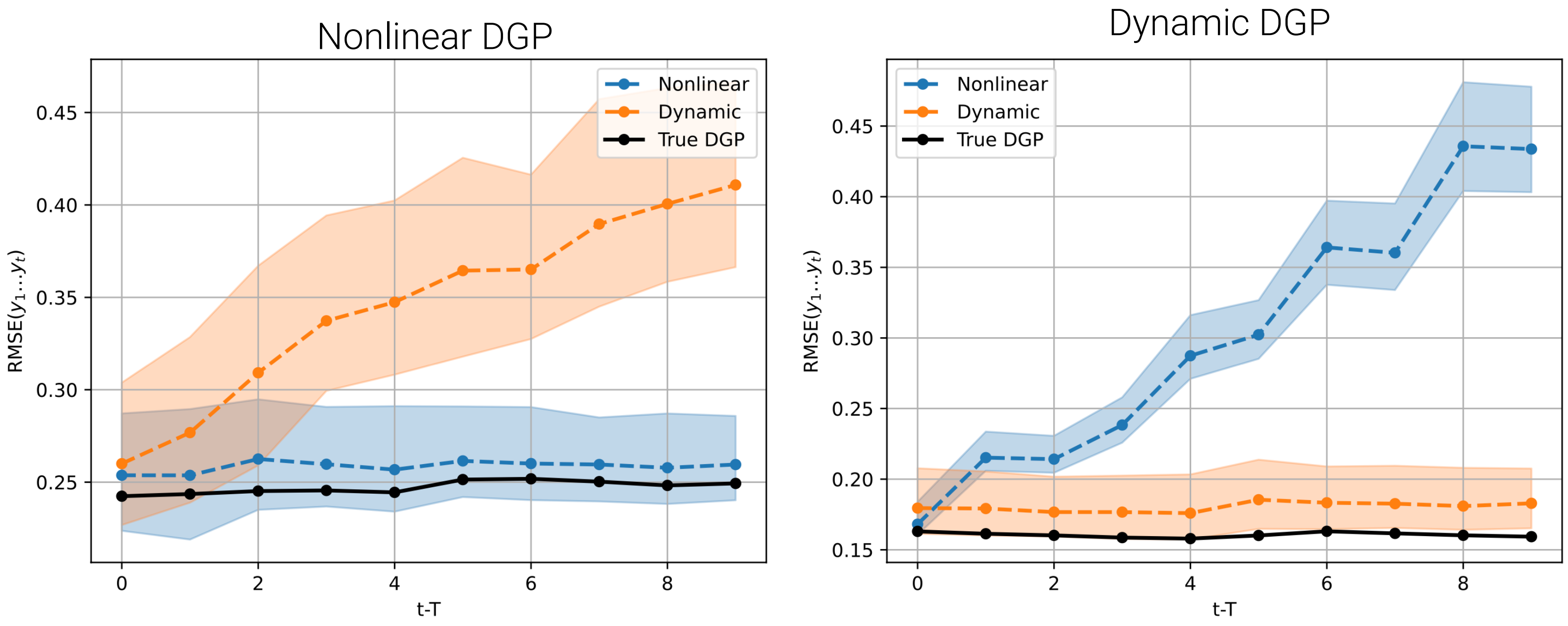
Test 1: Maximal Separation

Set spending next period to maximize the difference in predicted values across the two models



Test 2: See-saw

Rapidly changing spending across adjacent periods can break some of the common causes of conflation



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