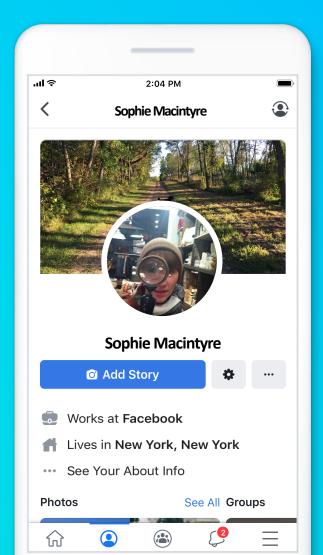


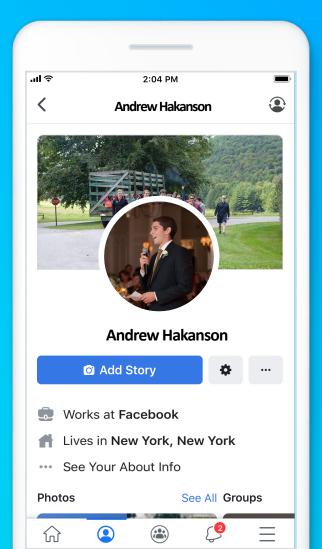
#### **SOPHIE MACINTYRE**

Ads Research Lead



#### **ANDREW HAKANSON**

**Marketing Science Partner** 



# AGENDA

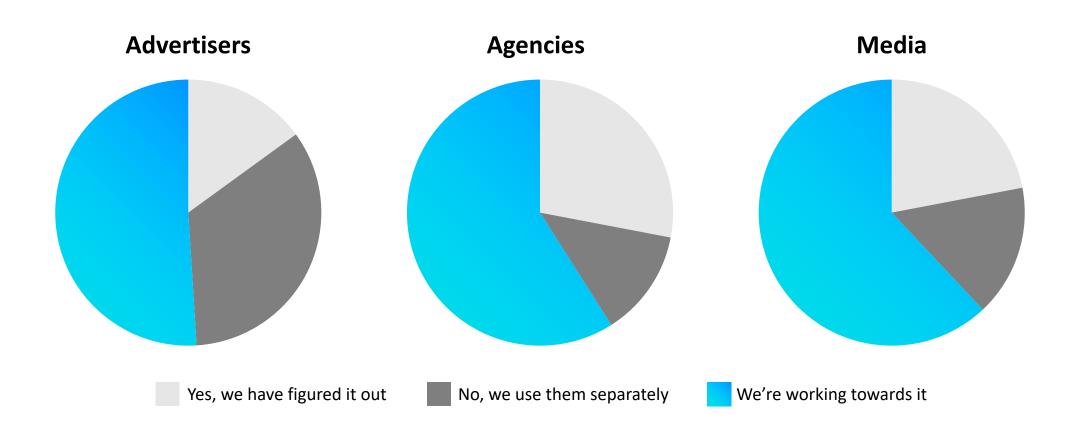
Calibration methods

2 Applied example

**3** Considerations and limitations

## Measurement is fragmented

"Does your team have a good sense of how to integrate marketing ROI results from measurement such as Marketing Mix Modeling, Multi-Touch Attribution or a unified measurement solution?"



# **Calibration with experiments**

A process in which experimental estimates are used as ground truth to validate or tune a model

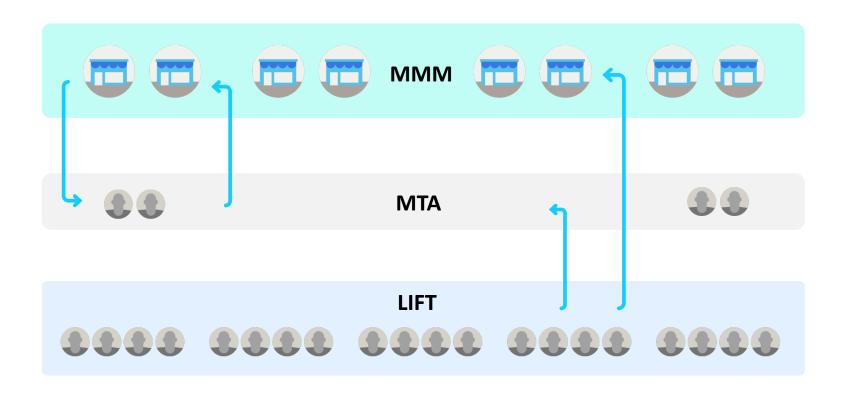
# Calibration increases incrementality of modeled results

#### **Incrementality**

The degree to which a measurement method estimates the true causal effect of an isolated marketing activity

Calibration allows advertisers to advance along the incrementality spectrum without abandoning existing measurement systems

#### Calibration can unite MMM and MTA

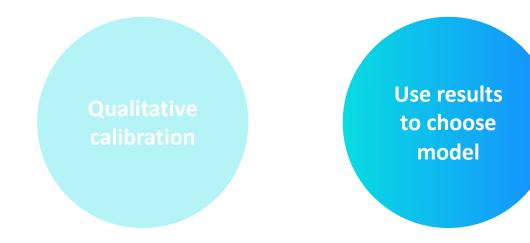


Using the same ground truth for both models can help make results more consistent

MMM, MTA and lift work together to create a powerful analytic toolset



<sup>\*</sup> Based on a survey of subject matter experts and available case studies



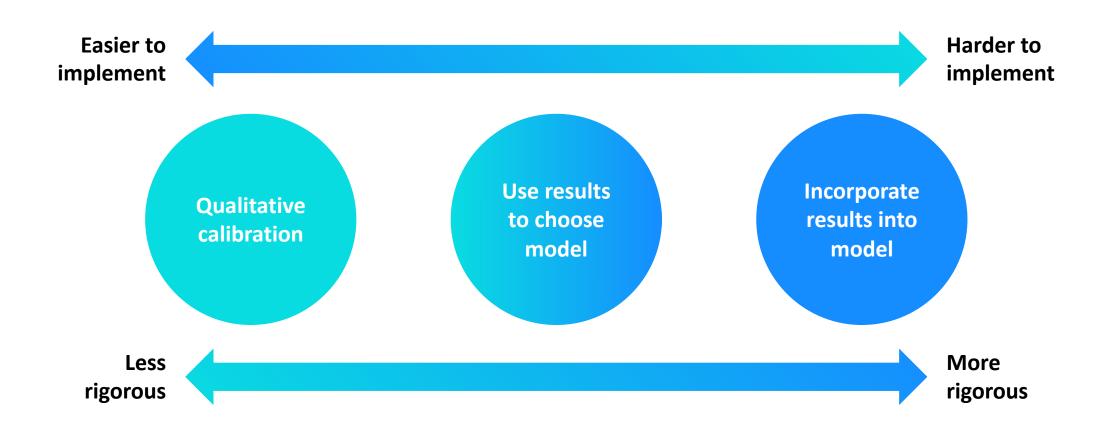
<sup>\*</sup> Based on a survey of subject matter experts and available case studies



Use results to choose model



<sup>\*</sup> Based on a survey of subject matter experts and available case studies



<sup>\*</sup> Based on a survey of subject matter experts and available case studies

### **Case study**







# ThirdLove is a growing eComm advertiser designing bras and underwear fit for every woman



Alignment of marketing and measurement strategies



Desire to understand the true business impact of their marketing spend



A culture of testing and learning



by Erica Mason | emason@thirdlove.com

# How ThirdLove calibrates MMM

Informed model selection based on lift tests:

Various models are backtested against a forward-looking holdout period to determine % error (actual vs. predicted)

Cost per incremental acquisition (CPIA) are determined from lift tests

Instead of choosing model based on % error, the CPIA is used in context to determine the 'best fit' MMM model







#### Various models are backtested

Models differ by variable transformations to ad stock and saturation

#### Models vary by channel

	Channel 1	Channel 2	Channel 3	Channel 4
1	No scaling	No scaling	No scaling	No scaling
	Add 7 day decay			
2	Scale by 5000	Scale by 5000	Scale by 5000	No scaling
	No decay	No decay	No decay	Add 7 day decay
3	Scale by 15000	Scale by 15000	Scale by 15000	No scaling
	Add 4 day decay	No decay	Add 4 day decay	Add 7 day decay

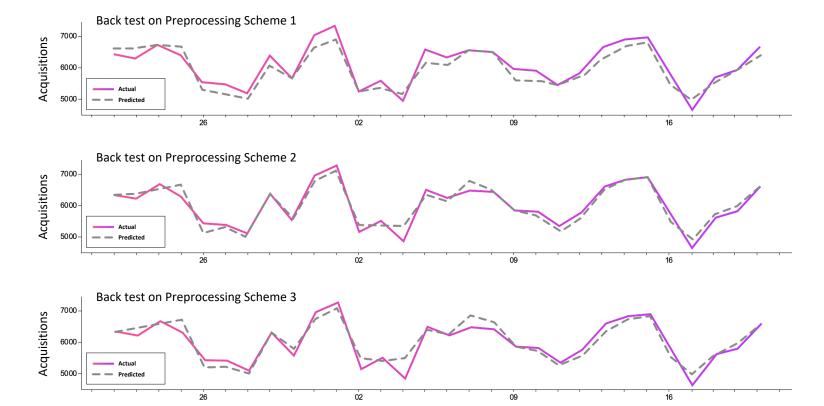
Table 3: Table to show the preprocessing treatment to deal with saturation and acquisition delay for each channel for three models



#### Various models are backtested

Models differ by variable transformations to ad stock and saturation







# Aligning backtest error with lift

Model #3 is selected instead of #2 since it aligns more closely to lift test, despite higher % error

	Backtest Result  – Daily MAPE	Channel 1 CPIA/MCPA	Channel 2 CPIA/MCPA	Channel 3 CPIA/MCPA	Channel 4 CPIA/MCPA
Model 1	3.6%	\$20 / \$229	\$12 / \$117	\$16 / \$153	\$24 / \$269
Model 2	2.5%	\$69 / \$148	\$52 / \$127	\$50 / \$125	\$148 / \$257
Model 3	3.1%	\$48 / \$65	\$65 / \$131	\$41 (\$70	\$130 (\$226
Model 3	3.1%	\$48 / \$65 	\$65 7,\$131	\$417,\$70	\$130

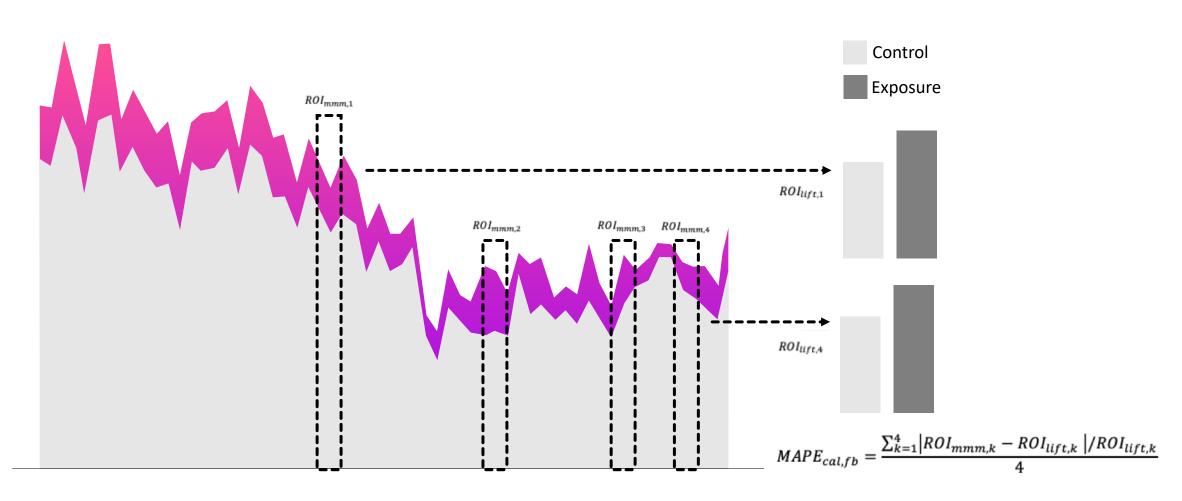
Table 4: Cost Per Incremental Acquisition (CPIA) and Marginal Cost Per Acquisition (MCPA) estimates for each channel from 2018-02-01 to 2018-03-01 for three models built with different preprocessing of spend data according to Table 3.

	Click Attribution form Channel Platform - CPA	Holdout Test Results - CPIA
Channel 1	N/A offline channel	No test data
Channel 2	\$36	\$66
Channel 3	N/A offline channel	\$39
Channel 4	\$96	\$128

Table 5: Cost Per Incremental Acquisition (CPIA) and Marginal Cost Per Acquisition (MCPA) estimates for each channel from 2018-02-01 to 2018-03-01 for three models built with different preprocessing of spend data according to Table 3.

# What if I have multiple experiments?

MMM Model #10 Base + other media Facebook



# What if calibration results disagree?

#### Match decision rule to advertiser priorities – some options:

- Spend/importance weighting
- Minimize sum of squared error

#### **Mean Absolute Percent Error (MAPE)**

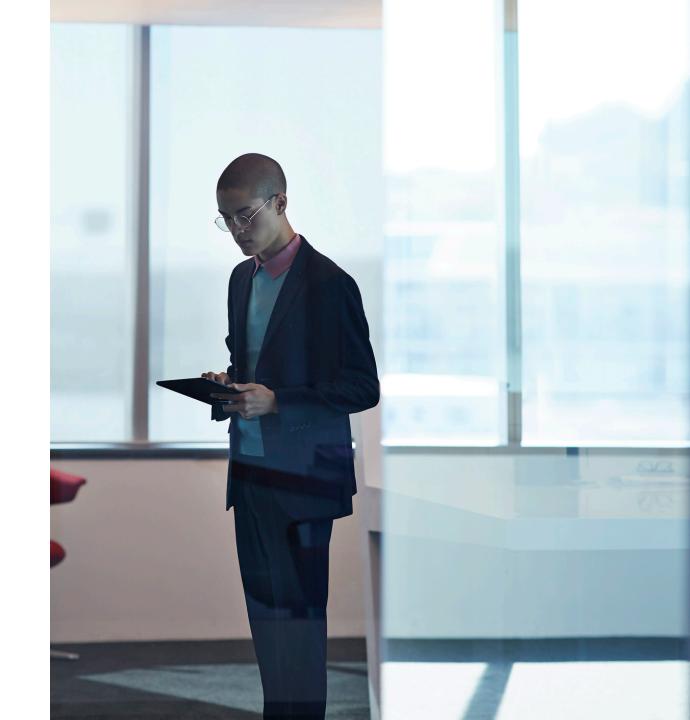
Model	Channel 1 65% of spend	Channel 2 30% of spend	Channel 3 5% of spend	Average	Spend Weighted	SSE
1	3	22	20	15	(9.55)	893
2	14	15	16	15	14.40	677

<sup>\*</sup>Simulated data for illustration purposes

#### **Considerations**

#### When designing an experimentation plan:

- Specify model and experiment with equivalent:
  - KPI (e.g., Sales, Cost per acquisition)
  - Brand and product definition
  - Time period
- Use geo experimentation if Conversion Lift is not available
- Experimental results should be stat sig



#### Limitations

# Calibration relies on channels capable of running experiments:

- Calibrating available channels reduces overall model error
- Consider other types of experimentation (eg. geo-testing) when platform doesn't have experimental tools

Requires close coordination between MMM vendor, client and media partner



# **Takeaways**

- Calibration increases the incrementality of modeled results
- There are several ways to calibrate match approach to goals and capacity
- Make an experimentation plan to streamline comparisons
- Create value by starting with available channels, and add more as measurement evolves

#### Resources

ThirdLove Whitepaper

Building and Validating

Media Mix Models

https://fb.me/Thirdlove-MMM

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and
Validating
Media Mix
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FBIQ Calibration Article

How to Calibrate

Marketing Mix Models

with Experiments

https://fb.me/CalibratingM MM



# THANK YOU

