

Where and how should we invest our next
Search euro?

1. Introduction

2. The Dilemma

3. The Insight

4. The Execution

5. The Results

6. Next steps

Introduction

The Team



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Lead Digital Marketing



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Channels:

Paid Search via Google and Microsoft

Display Retargeting via Meta and RTB

Comparison Engines: e.g. Beslist & Kieskeurig

Affiliate Marketing: e.g. Kleding.nl & Tweakers

App install campaigns

W.
G.R



For over 70 years, Wehkamp is
the department store for families
in the Netherlands.





1952



First advertisement as catalog business



1995



Wehkamp is first department store in NL with online shop



2008



From catalog business to fully online.



2021



Acquisition of kleertjes.com



2023



Introduction paid returns



2025

altijd
wehkamp sinds 1952

Building towards a bright future!

Wehkamp in short

>400k
items

1.700
brands

2.3 mln
active
customers

>375k
daily
visitors

44%
orders
via app

15%
of sales is
private label





home



beauty



garden



fashion



toys



baby

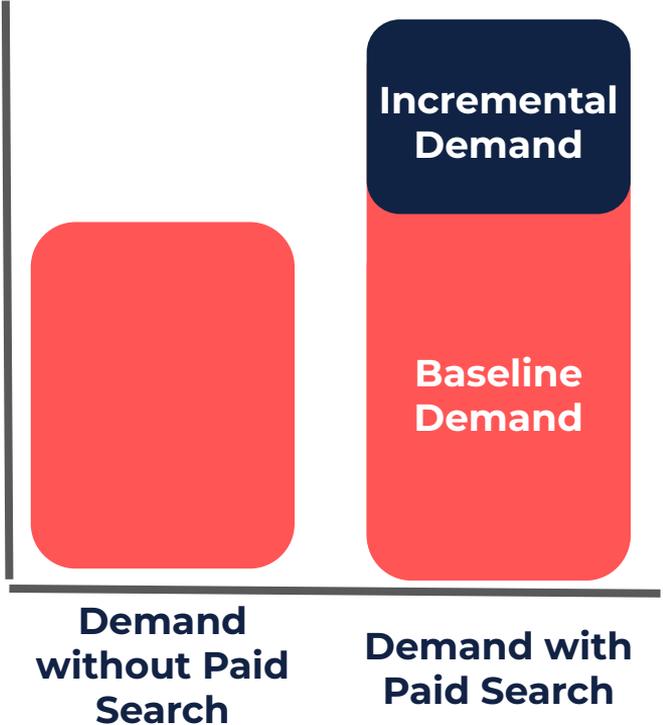


sports

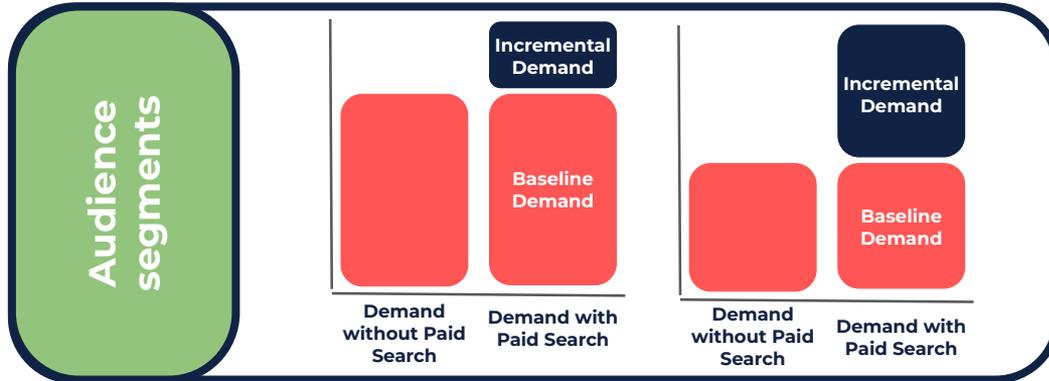
The Dilemma

“Half the money I spend
on advertising is **wasted**;
the trouble is I don’t
know **which half.**”

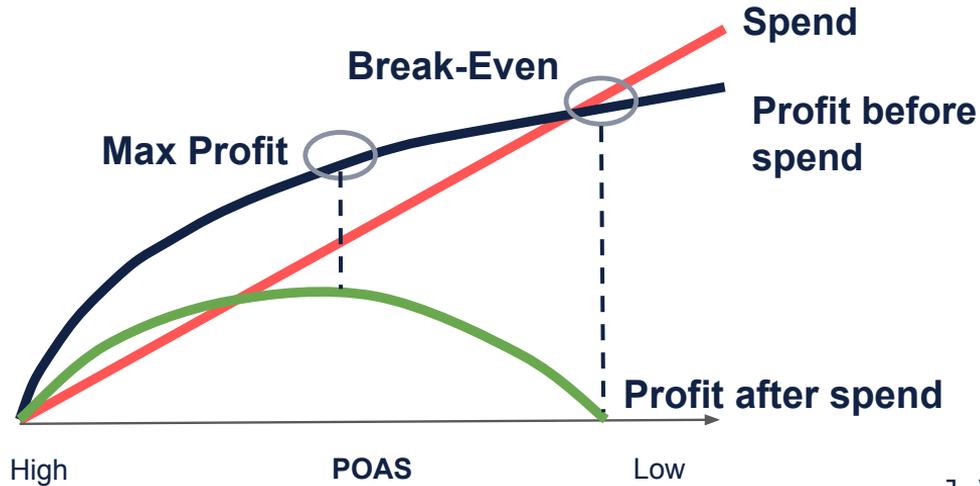
There's baseline demand and there's demand driven by Paid Search



Across categories and audience segments this can differ heavily



Result diminishes with spend increment



1. Where are we on this graph across our categories and customer segments?
2. And what is the additional value of last spend Euro?



**So, where should we invest
this next Search Euro?**

The Insight

“Meten is weten”

Exploring the elasticity of Paid Search by increasing spend in a test region

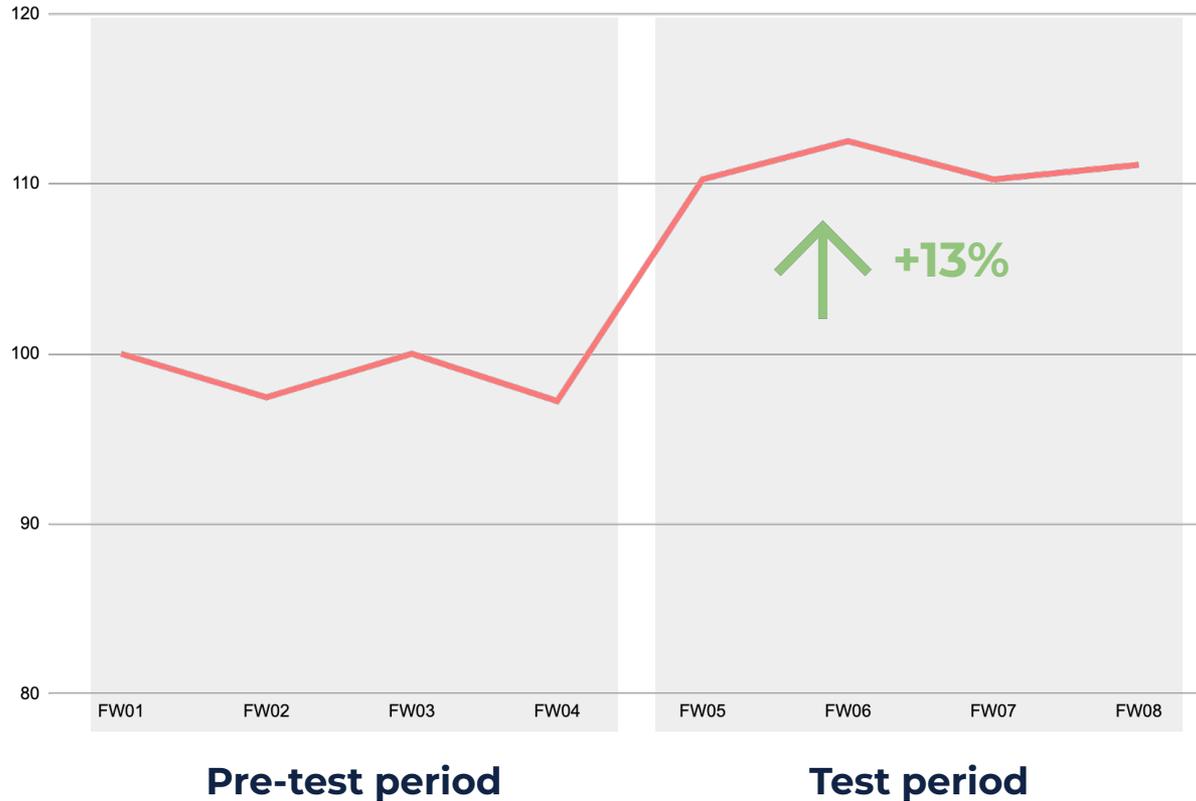
Control Region
Business as usual



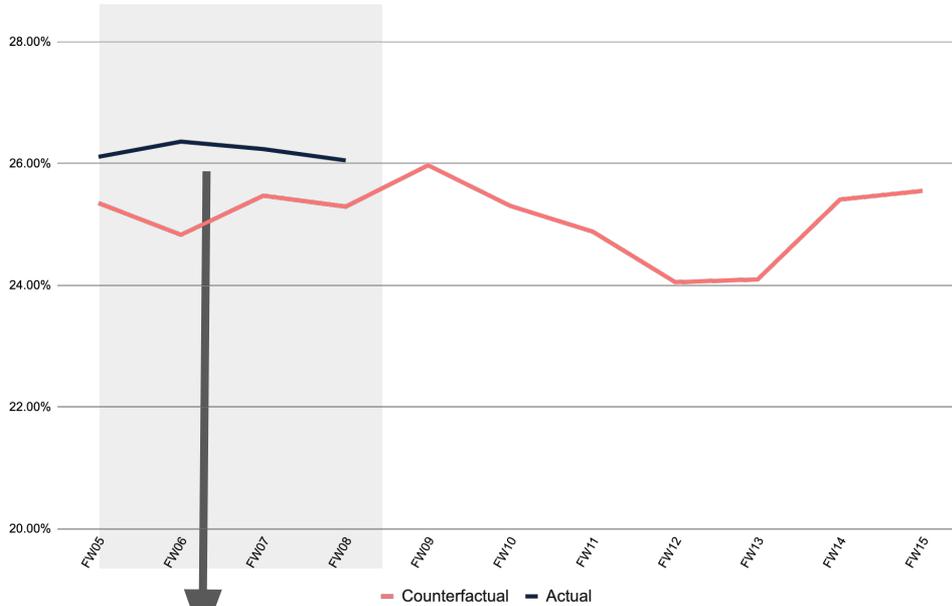
Test Region
Spend x 1.5



Immediate impact on avg. CPC in test region vs. control region



Increased spend let to a rise in demand share test region vs. counterfactual



Incremental uplift

+7.7%

+4.5%

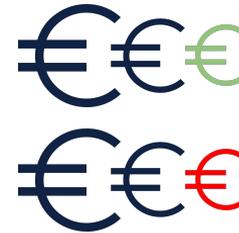
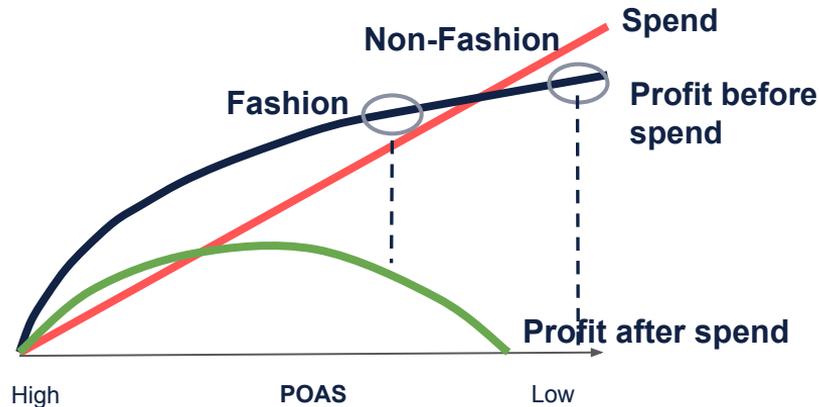
Incremental results from increased spend differ from attributed results

Test vs. Control	Clicks	Costs	Profit	Add. POAS
Attributed Results	+41%	+59%	+56%	1.58
Incremental Results			+4.5%	0.87

Attribution counts **every touchpoint**;
Incrementality only counts **the 'Lift'**.

Increased spend was still profitable on fashion, but wasn't on non-fashion

Incremental results	Add. POAS
Fashion	1.45
Non-Fashion	0.6



The audience segments showed different responsiveness to the spend increasement

Test vs. Control	Demand	Profit
Loyal customers	+3%	+1.7%
Not-so-loyal customers	+9%	+10.5%
Inactive customers	+8.6%	+9.4%

Also, paid search drives customer inflow →

**+15% in
new
customers**

Key takeaways

Incremental lift

Spend increase showed incremental lift; orders **+2.5%**, demand and profit **+4.5%**.

Map elasticity across categories

Discovery of under-investment in almost all fashion categories (with the exception of seasonal beachwear). Relative impact on Non-Fashion is higher, but wasn't profitable.

Map elasticity across audiences

Validation of the 'loyalty paradox' with significantly lower responsiveness to paid search (**+3%**) vs. not-so-loyal and inactive segments (**+9%**). Also paid search drives customer inflow (**+15%**)

Actions



Incorporate category elasticity insights into steering.



Incorporate audience elasticity insights into steering.

The Execution

Elasticity insights strategic framework

	Fashion (High Elasticity)	Non-Fashion (Profitable baseline)
Spend baseline	Increase baseline (ERS)	Continue deep baseline (ERS)
Loyal customers	Reduce spend	Minimum spend
Not-so-loyal / Inactive	Increase spend	Maintain spend



New customers:

As audience segmentation is done on recency and frequency; we want to use lifetime value per category to steer on new customers.

Scaling Fashion, sustaining Non-Fashion: the audience strategy →

	Fashion (High Elasticity)	Non-Fashion (Profitable baseline)
Loyal customers weight	x0.6 (Reduce spend)	x0.75 (Minimum spend)
Not-so-loyal / Inactive weight	x2.0 Increase spend	x1.75 Maintain budget

We started by using Google's value rules adjustments

Primary condition Select your rule's primary condition

Audience segment ▾

All audience segments
 Enter audience segment

Search	Browse	1 selected
<input type="text" value="rfm"/>		Customer lists
<input type="checkbox"/> DB - rfm_09_at_risk		
<input type="checkbox"/> Customer lists DB - display_rfm_kids		<input checked="" type="checkbox"/> DB - rfm_01_champions
<input type="checkbox"/> Customer lists DB - display_rfm_mens		
<input checked="" type="checkbox"/> Customer lists DB - rfm_01_champions		
<input type="checkbox"/> Customer lists DB - rfm_04_promising		
<input type="checkbox"/> Customer lists DB - display_rfm_ladies		

Secondary condition Select your rule's secondary condition

Select condition ▾ Clear selection

Value adjustment Select the value adjustment that will apply to your base conversion value

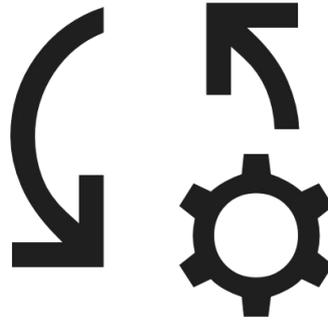
Multiply ▾

Perk: adjusted value at the moment of auction.

Downside: just the coverage of Google's matching **~20% of auctions**

A more sustainable approach was to leverage our steering structure

Consented
GCLID's via
server-logging



Proprietary
**Multi Touch
Attribution
Profit** model



No attribution finds
place in GAds



	Fashion (High Elasticity)	Non-Fashion (Profitable baseline)
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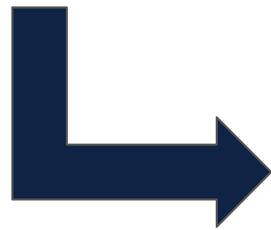
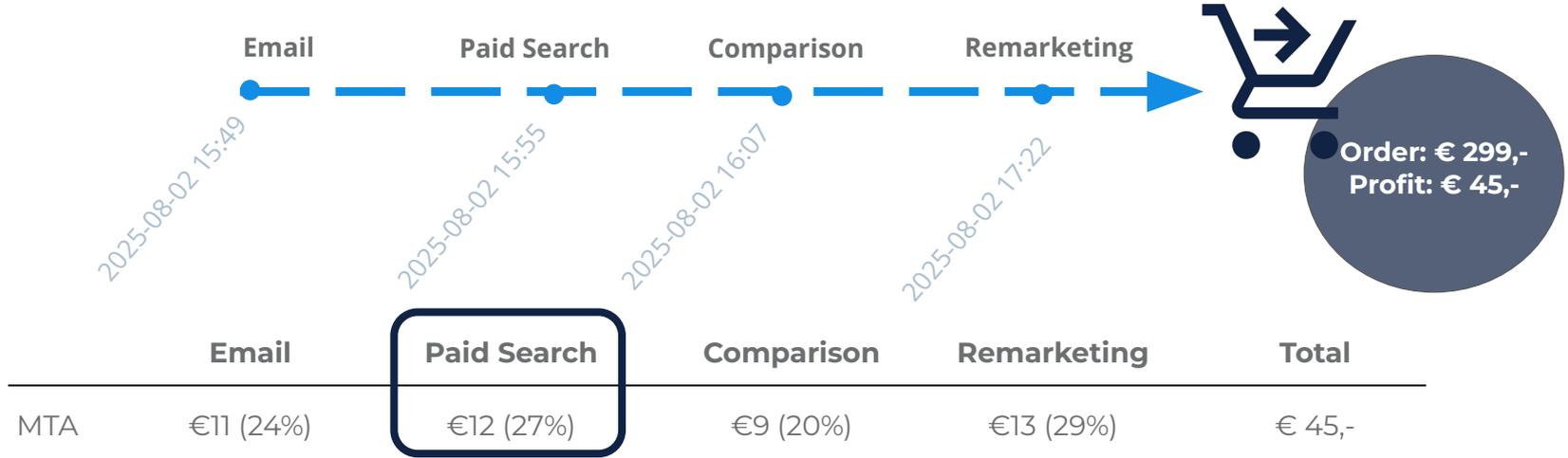


Adding dynamic
weight to
attribution

100% of consented
orders get value
adjustment

Loyal customer buys fashion

>=4 orders <180 days

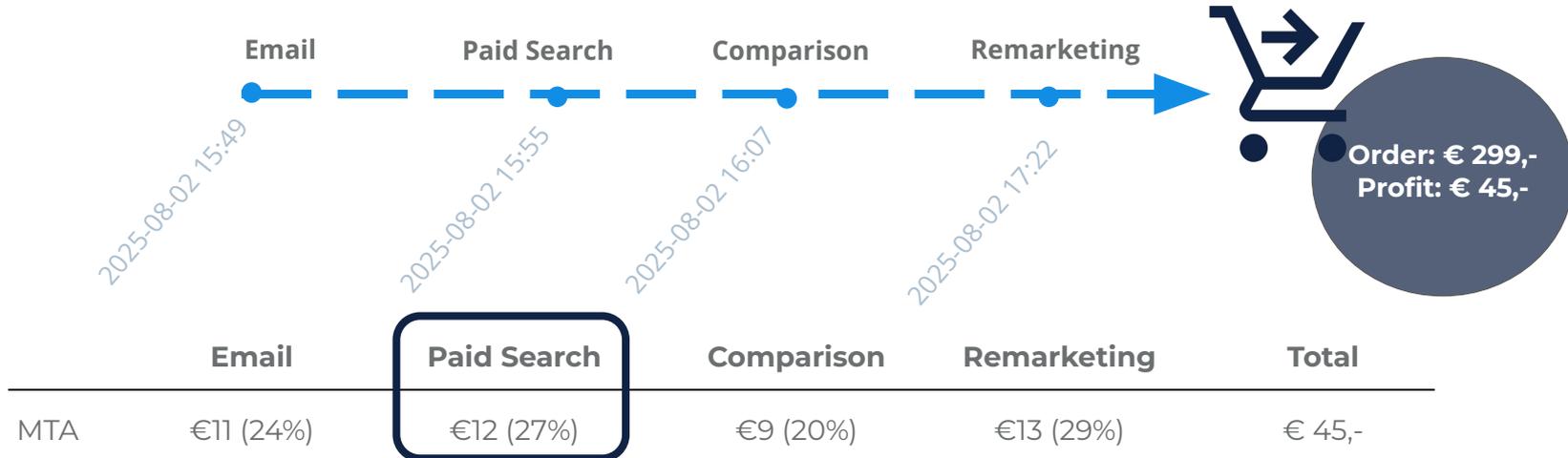


New attributed value

$$€ 12 \times 0.6 = € 7.2$$

Inactive customer buys non-fashion

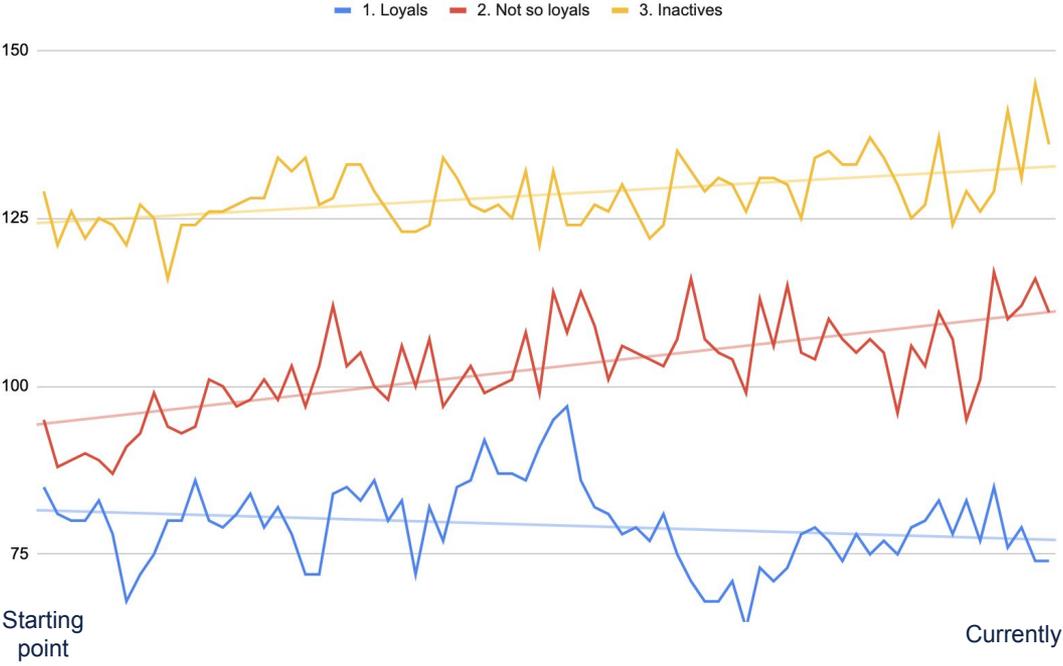
0 order >365 days



New attributed value

$$€ 12 \times 1.75 = € 21$$

Desired impact on audience CPC vs. overall CPC development



For new customers we utilized Google's new customer acquisition goal

New customers ^

1. Add an incremental conversion value for new customers (regular)

This amount increases the conversion value for a new customer over an

€ 7.55 Use suggested value: €18.26

Recommended value is based on your average purchase conversion value

 Calculate your value

Adding the future value of new customers per category

Guardrails to prevent over- underinvestment

- Weighting creates feedback loop: Multipliers recalibrate as audience sizes evolve.
- Working with multiple campaign layers and CSS's.
- Audiences share of clicks within categories vs. baseline.
- Own server-logging data of audience segment shares from Paid Search.
- Frequently elasticity testing.

The Results

Driving profitable growth: Delivering higher volume at increased efficiency

	Fashion (High Elasticity)	Non-Fashion (Profitable baseline)
Spend baseline	Increase baseline (ERS)	Continue deeper baseline (ERS)
Loyal customers	Reduce spend	Minimum spend
Not-so-Loyal / Inactive	Increase spend	Maintain budget

+

NCA



Demand YoY: **+11%**



Profit YoY: **+15%**



POAS YoY: **+2%**



Reactivation YoY: **+11%**

Next steps

Next steps

Incorporate new customer value in MTA profit upload

With decreasing match rate on customer match lists it becomes increasingly harder for Google to identify new customers.

Continue seasonal elasticity tests

Validation of spend levels is highly impacted by the season. We're aiming of making elasticity testing a quarterly, structural way-of-work. Also seasonal categories like Beachwear or Garden need to be tested in certain seasons.

Integrate stock insights into steering

Focusing marketing pressure on high-availability inventory to lower spend on high velocity items.

Expand to full funnel

Use the Search elasticity insights to inform upper-funnel budget allocation, ensuring we drive demand where we know the 'pull' is most incremental.

dankjewel
thank you