Practice papers

A new model for optimal advertising impression allocation across consumer segments

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Abstract With conflicting recommendations and marketer practices about advertising impression allocation approaches (ie 'the media strategy'), from approaches centred on reach ('go broad') versus targeting ('get specific'), the debate rages on: 'Are marketers targeting too much, not enough, or simply targeting the wrong consumers with their advertising?' This paper interprets the issue of targeting as an advertising impression allocation question and instead of leading with case study evidence which by its nature is parochial, uses a novel mathematical approach to create an ad impression allocation model based on probability of choice. This contrasts with broad reach strategies and is different from other targeting schemes, eg key demographic, high lifetime value consumers, non-buyers for conquest, proprietary segments of interest. The findings suggest that targeting Movable Middles, ie those with a 20–80 per cent probability of choosing the brand of interest, can lead to 50 per cent improvement in return on ad spending (ROAS) versus broad reach media plans. The results are then supported with two in a large scale market case study. The Movable Middle, a segment of category buyers with a 20–80 per cent probability of choosing a brand, are shown to generate 2–23 times more ROAS than other category buyers who are mostly non-buyers of a brand. This pattern was uncovered mathematically but then subsequently verified empirically. By shifting about 10 per cent of ad impressions to audiences that have high concentrations of Movable Middles, a typical 10 per cent share brand can expect a 50 per cent improvement in campaign ROAS and a 13 per cent improvement in converting non-buyers. This leads to better serving brand needs for both quarterly sales and for long-term growth via customer acquisition. This new media strategy is not just limited to digital campaigns; it can be implemented across any media channel, including linear TV, radio and print.

KEYWORDS: advertising, targeting, Movable Middle, lift, media strategy, return on ad spending (ROAS), probability of purchase

INTRODUCTION

Marketers receive conflicting advice from experts regarding optimal advertising impression allocation strategies for their advertising. Reach and targeting are prominent advertising allocation strategies, but they are contra-indicated as the former will call for a broad dispersion of ad impressions to get as many eyeballs as possible to see the ad while the latter calls for differentially higher media weight against consumer segments who are thought to have a higher probability of responding. In practice, marketers may hedge their bets on the two ideas, eg by employing broad guidance principles for buying mass media while bolting on funds for programmatic advertising that might have more precise targeting rules.

The case for reach. One school of thought[1] believes that targeting is counterproductive[2] and the best approach is to buy as much reach as the marketer can afford. This is largely motivated by noting the highly correlated positive relationship between brand penetration and brand market share[3] and making the seemingly logical connection between broad reach and a goal of maximising penetration. A positive correlation between media plans that maximise reach and brands exhibiting long-term growth trends has also been noted.[4] In fact, it is common for marketers to want to measure the reach of their advertising.[5]

The case for targeting. A number of marketing research providers[6] have advised marketers to target consumers who are vulnerable, persuadable, or fence sitters.[7] In practice, the addressability capabilities of the digital world have led to much advertising being targeted to segments defined on behavioural and/or demographic factors. In politics, advertising is always focused on swing states/districts and independent voters.[8] Programmatic advertising,[9] which is the practice of targeting an ad to a specific recognised consumer ID, now accounts for 87 per cent of digital display ad spending[10] and addressable television ad spending has grown 33 per cent.[11] Procter and Gamble, for example, has announced that it targets advertising based on propensity modelling.[12]

Several studies that are in practitioner literature (eg white paper form) report that ROAS (return on ad spending) can be wildly different as a function of the consumer segment exposed to advertising. For example, the 2017 white paper, 'The Persuadables'[13] documents that a segment called 'Persuadables', defined as heavy brand buyers who are probabilistically close to an upcoming purchase, exhibited an average (across three CPG [consumer packaged goods] campaigns) of 16 times higher ROAS versus those not in the segment, in response to the same advertising creative. NCS (Nielsen Catalina joint venture), which operates a frequent shopper database of ~90 million shopper IDs at a household level, similarly found that ad responsiveness from brand buyers (versus non-buyers) was multiples higher,[14] on average.

Well before the digital age, evidence had been published suggesting that response elasticities can be expected to vary substantially across individual consumers as a function of brand loyalty.[15]

Who to target. Despite the recommendations of Byron Sharp,[16] Les Binet and others who suggest 'buy the most reach you can afford', most marketers believe that not all consumers are created equal and have conducted market research segmentation studies accordingly to find their target segments. However, that is where the agreement ends. Should they target proprietary segments, the heavy buyers and/or those with high lifetime value as Professor Peter Fader recommends?[17] Many marketers still target a coveted age demographic. Another common practice is to direct ad impressions to non-buyers and suppress ad impressions going to existing buyers or simply not share their first party customer lists with large publisher platforms. The main motivations to suppress existing customers from paid advertising are:

1. 'We e-mail our customers, so we do not have to use paid media.'
2. 'We do not share customer lists due to privacy concerns.'
3. 'Our main focus for paid media is to grow our customer base so we want to deliver advertising to non-customers we hope to conquest.'
4. 'We view certain of the largest digital publishers as our competitors and do not want to share our customer lists with them.'
5. As reported by a digital consultancy Delve,[18] efficiency of media spending is thought to be improved by not marketing to consumers who might have already bought, as StubHub was reported to discover.

Still, other marketers specifically push a first-party customer list for paid media activation.

With conflicting ideas, the question remains: 'Are marketers targeting too much, not enough, or simply targeting the wrong consumers with their advertising?'

A renewed focus on brand loyalty. We were motivated by theories that, at an aggregate level, advertising elasticity is inversely related to levels of brand loyalty, notably proposed by the Hendry Corporation.[19] We wanted to explore if this relationship applies at an individual consumer level, or if it still holds at all. We note empirical studies that are directionally consistent with the idea that a consumer's level of probability of buying a brand influences their responsiveness to advertising exposure. For example, literature has reported[20] increased sales response in the 18 per cent range by targeting switchable customers with extra marketing. However, we did not find persuasive work that gives a mathematical reason for this pattern which makes it hard to accept this collection of works as generalisable.

A path forward based on maths, verified by in-market evidence

We sought to determine a mathematical basis for understanding if a connection between individual consumer brand loyalty and advertising responsiveness exists. Here, we define loyalty as the degree of restrictions in brand to brand switching versus random patterns.[21] If found, this would allow a marketer to build targeting into their media planning stage and reap the full benefit, rather than waiting for campaign results and doing a post-mortem.

We chose a mathematical approach that brings together in a novel way three well-known modelling approaches.

1. Logit models[22] often used in MTA (multi-touch attribution modelling)[23] to describe response to advertising as a function of a consumer's baseline probability of converting plus the effects of advertising exposure.
2. A Beta probability distribution that describes the density function of consumers' baseline probability of choosing a given brand.[24]
3. Agent-based modelling, where more than 600,000 virtual consumers were created, and rules of buying and ad responsiveness were embedded in each agent that aggregate back to known market shares and patterns of buying and ad impressions delivery. Distribution of ad impressions and when category buying occurred for each virtual consumer were achieved via Monte Carlo simulation techniques.[25] We also verified that the response curves we were getting as a function of incremental ad exposure at different baseline probabilities matched closely to the expected rate of change at each of those points along the curve by taking the first derivative of the logit function, evaluated at different points on the curve (eg low baseline probability of choosing the brand such as 5 per cent, moderate such as 50 per cent, etc).

By bringing these three models together, we can compare and contrast, for example, how those with a 0–5 per cent probability, versus a 50–55 per cent probability of choosing a brand are expected to respond to the same tranche of advertising distributed the exact same way across channels and weeks.

INTRODUCTION TO OUR TEST PRODUCT CATEGORY

Numerator provided the authors with receipt scanning data from 2018–19 on several CPG product categories. We chose the number three brand of frozen pizza as a prototypical brand within a prototypical CPG category.

We analysed 15 months of data from 63,345 cooperating consumers who bought frozen pizza two or more times during this timeframe.

This category is fragmented with 11 major brands, with the leading brand having a 17.8 per cent share of purchases and the smallest significant brand having a 1.7 per cent share. The brand we analysed as number three in the category had a 10.2 per cent share.

The average category purchase cycle is in the one to two months range across all 2+ category buyers.

Brand repeat rates are moderate, ranging from 22 per cent (smaller brand) to 55 per cent (market leader), indicating that consumers exhibit brand preferences, but also noted is that they switch among a large consideration set. For our brand of interest, 80 per cent of their buyers also bought one to four competitive brands and 15 per cent bought five or more competitors. Exclusive brand buyers only accounted for 4 per cent of brand sales. This was a typical pattern although we observe that the smaller the brand share, the larger the consideration set tends to be.

There is ample evidence that advertising can influence this variability in brand purchase outcomes from purchase event to event.[26] We sought to understand better how advertising exposure might influence individual consumers differently and in predictable ways. This understanding would give marketers a roadmap for how their strategy for allocating advertising impressions could be adjusted to have an even greater positive effect.

MODEL BUILDING PHASE

Our exploration of optimal advertising allocation strategies began with specifying an objective function.

Objective function

Mathematically, we are attempting to find the allocation across consumers of a fixed number of ad impressions which will result in maximising expected ROAS [27] for those impressions. Solving for reach would be one allocation approach; the set of targeting schema represent other possible allocations. To guide our search for optimal allocations, we develop the following equation structure.

ROAS is defined by equations (1a, 1b):

$$\mathrm{ROAS} = \mathrm{R}/\mathrm{M} \tag{1a}$$

$$\mathrm{R} = \mathrm{PPC}^{*}\mathrm{C} \tag{1b}$$

where:

R = incremental revenue during time period t caused by M

M = incremental ad spending during time period t

PPC = average sales revenue from incremental conversions

C = the absolute quantity of incremental sales or conversion events caused by M

We simplify expected ROAS, E(ROAS), as a function of increases in the vector of *p(i)*, the probability that consumer *i* chooses the brand of interest on a given category purchase, by defining the expectation as referring to the next purchase in a time-independent manner (see equation 3). We also treat the vector of *p(i)* for all *i*, defined as the probability of consumer *i* choosing the brand of interest on a given category purchase occasion, as stationary[28] except as 'disturbed' by incremental advertising exposure. We make the typical assumption for models that assume stationarity that a brand's share will eventually go back to its baseline if the incremental advertising is eliminated (ie advertising effects are reversible).

The typical model of how advertising can disturb individual consumer purchase probabilities is notably documented as a logit model[29] and used extensively in practice by academics and practitioners[30,31] and by service providers of MTA modelling of digital conversion data (see equations 2a, 2b).

$$\ln\left[\mathrm{p(i)}/(1-\mathrm{p(i)})\right] = \mathrm{u(i)} + \Delta\mathrm{u(i)} \tag{2a}$$

where:

p(i) = the probability of consumer *i* buying the brand of interest on a given category purchase occasion

u(i) = baseline stationary utility scaled to return the stationary *p(i)*

Δu(i) = increment in utility that is caused by exposure to advertising impressions

This model form nicely leads to linear regression, where the probability of conversion is correctly bounded between 0 and 1, and it also lends itself to maximum likelihood estimation when the observed outcomes (ie, dependent variable) data at a consumer level are {0,1}; ie convert or not convert.

Through rearranging terms, this gives us the well-known logit equation:

$$p(i)^{\star} = \exp\left[u(i) + \Delta u(i)\right] / \left\{1 + \exp\left[u(i) + \Delta u(i)\right]\right\} \quad (2b)$$

We treat maximising E(ROAS) as equivalent to finding the best allocation of a given quantity of advertising impressions ('the media strategy') for maximising E(C), that is the expected number of incremental conversions caused by a fixed M (equation 3)

$$E(C) = CPC^{\star} \sum_{i}^{N} \left[p^{\star}(i) - p(i) \right] \quad (3)$$

where CPC = the average number of category purchases per category buyer during the campaign period, $p^{\star}(i)$ is the 'disturbed' probability of purchase given some amount of ad impressions delivered to consumer i, and N is the number of consumers. Note that we have treated CPC as a constant, as the covariance of buying rates to $p(i)$ is mild as per receipt scanning data.

To help us find an optimal allocation, we consider this as a marginal return problem,[32] ie which consumer would be expected to deliver the greatest increase in E(C) if shown the next ad impression. Under the condition that ad impressions are broadly distributed, this is equivalent to finding the maximum point of the first derivative dp/du at stationarity (equation 4):

$$dp/du = p \star (1 - p) \quad (4)$$

where this function is maximised when $p(i) = 0.5$ as seen graphically in Figure 1.

As an illustration, we can compare consumer A who has a 50 per cent probability of buying brand (j) to consumer B with a 2.5 per cent probability. Not only is their baseline probability 20 times different, but the ROAS of serving advertising to consumer A is expected to be 10.3 times greater versus Consumer B as well, based on equation (4). (This assumes little or no incremental upcharge for targeting consumer B which is reasonable

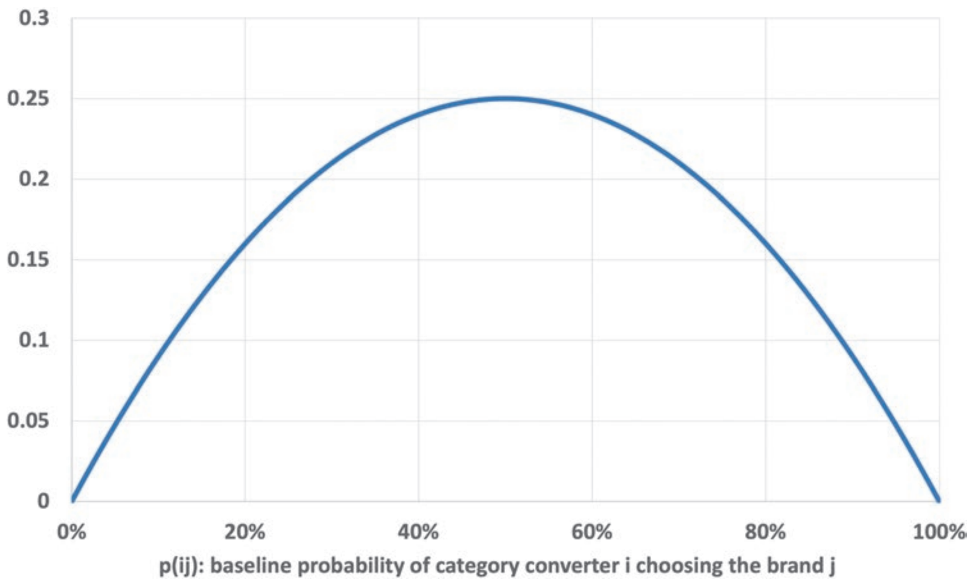

Figure 1: First derivative of brand conversion probability *f(p)* with respect to *u*

given the infrastructure for targeting would already be in place, even if marketers often define their target in sub-optimal ways.)

While it is obvious that someone with extremely high loyalty to a given brand cannot increase their probability of choosing the brand of interest much in response to advertising (as they are capped at 100 per cent), the property of symmetry of the first derivative leads to a surprising finding — non-buyers of a brand are also expected to be extremely unresponsive to small infusions of a brand's advertising! This is contrary to the narrative that many marketers express, namely that incrementality will come from exposing non-buyers to advertising impressions.

The literature provides strong empirical support that those with a mid-range probability of choosing a brand (versus its direct competitors) are also most responsive to advertising. This is implied by the work of Guadagni and Little. Gensch found that switchers were most responsive to marketing outreach for industrial products.[33] Another study found that prior levels of buying from a catalogue were positively correlated and predictive of response to a marketing event and that those who had little response in the past also had an extremely low probability of responding to an event such as a mailed catalogue.[34] While they used a discontinuous modelling approach rather than a logit model formulation, they similarly found that those with a low history of buying have a low probability of responding to marketing.

Targeting appears to be best because prior expectations of ad responsiveness are, in fact, highly differentiated. Going back to our consumers A and B, let's assume that their responsiveness to advertising is governed by the first derivative of the logit. Even assuming diminishing returns to frequency of ad exposure based on geometric decay, of say 0.8 (for example, the third impression is worth 64 per cent of the first impression), marginally, the 10th impression to Consumer A (50 per cent probability of buying) will have a slightly greater effect than the first impression to consumer B (0.025 per cent probability of choice).

Generalising, equation (4) describes expected heterogeneity of a given consumer's response to advertising impression exposure. Combined with Beta distributed heterogeneity to baseline probabilities of purchase, this becomes the basis for finding more optimal targeting strategies than going for the broadest reach. A broad reach media plan would only be optimal if a marketer's prior expectation of consumers responding to advertising was a uniform distribution which it clearly is not.

Moving from point estimates to ranges

In practice, targeting requires a segment of reasonable scale. Here, we identify a segment that we call 'the Movable Middle', defined as category buying consumers who have $0.2 <= p(i) <= 0.8$. Accordingly, we also define Low Loyals as those who have the probability of purchase below 20 per cent and High Loyals as those with the probability of purchase above 80 per cent. Not only is the Moveable Middle segment interesting in terms of its likely greater responsiveness to advertising but they also contributed two and a half times as much to brand sales as their incidence in the category buyer universe; in other words, these consumers form a very important buyer segment.

To estimate the prior expectation of response to advertising for this broader segment, we must also specify the probability distribution that we are, in effect, integrating over this range.

A well-known probability distribution for probabilities of purchase towards a given brand is the Beta probability distribution[35] where the two parameters, α and β can be directly solved for by knowing a brand's share of buyers and its repeat rate (ie per cent

Table 1: Correlation coefficients of the Beta distribution to actual five percentiles of share of requirements

		Share	Repeat rate	Correlation coefficient
Category 1 (9 brands)	Market leader	34.50%	64%	95%
	Smallest major brand	1.30%	26%	100%
Category 2 (16 brands)	Market leader	16.20%	47%	99%
	Smallest major brand	1.30%	26%	100%
Category 3 (9 brands)	Market leader	38.70%	63%	92%
	Smallest major brand	1.10%	26%	100%
Category 4 (10 brands)	Market leader	17.50%	48%	97%
	Smallest major brand	1.80%	41%	100%

Source: (Numerator receipt scanning data)
Share is defined as percentage share of category buying shopping trips where the brand was purchased.
Repeat Rate is defined as the per cent buying the same brand on consecutive category purchases.

buying the brand on consecutive purchases) which represent the first and second moments of the Beta distribution.[36] The Beta distribution and its moments are defined below (see equations 5a, 5b, 5c):

$$\text{Beta Distribution PDF} = f(p; \alpha,\beta) = p^{\alpha-1}(1-p)^{\beta-1} / B(\alpha,\beta); \quad p \in (0,1), \quad (\alpha,\beta) > 0 \tag{5a}$$

$$E(p) = \alpha/(\alpha+\beta) \tag{5b}$$

$$E(p^2) = [\alpha/(\alpha+\beta)] * [(\alpha+1) / \alpha+\beta+1)] \tag{5c}$$

where $B(\alpha,\beta)$ is the Beta pdf. In practice, α and β typically take on values such that this pdf is U-shaped; ie a high concentration of category buyers close to $p(i)=0$ and a small uptick for $p(i)>0.8$. Although well accepted in the literature, we validated the application of the Beta distribution to the distribution of purchase probabilities for 44 brands across four CPG categories by comparing modelled predictions to the distributions of share of wallet based on Numerator receipt scanning data. The Beta pdf fits extremely well across brands with a wide range of market shares; the correlation was over 99 per cent across 880 data points (44 brands $\times$ 20 percentile buckets) (see Table 1).

By the shape of the Beta distribution for our brand of frozen pizza, we had a preliminary expectation that the ROAS of the Movable Middle would be five times greater than the ROAS of consumers not in the Movable Middle but there were still a few potentially confounding factors to be considered.

MONTE CARLO SIMULATION PHASE

A fully explicated analytic solution to maximising ROAS is extremely complex and would obscure the simple core of the maths that is revealed by the first derivative of the logit function. For example, in practice, marketers cannot reach only Movable Middle consumers as this is a segment that is embedded at different density levels inside of targetable audiences. Furthermore, the audiences might have a variable probability of exposure based on their pattern of consuming the type of media where advertising is placed. Finally, we assume diminishing returns as a function of weekly ad impression frequency to a given consumer[37,38] and a time decay over weeks to advertising effects consistent with TransUnion (Neustar) normative relationships.[39]

Given all of these complexities, we created an agent-based model following best practices[40] and used Monte Carlo simulation to integrate media exposure and purchasing stochastic processes into the same model. We created an agent-based representation of the number three brand of frozen pizza which had a 10.2 per cent market share, 44 per cent purchase to purchase repeat rate, and a US$60m annual advertising budget to support US$400m revenue. Simulations were done within the framework of TransUnion's proprietary targeting system of 172 pre-defined consumer audiences.[41] We created and assigned 623,000 agents representing TransUnion's 126 million tracked US households. The brand was estimated to have a different market share in each of the 172 audiences based on consumer research, subject to its national averages from Numerator receipt scanning data.[42] Each agent's rules were governed by the following:

a) Agents were assigned a probability of buying the brand that would collectively return the desired Beta distribution for each of the 172 audiences.
b) A category purchase cycle for each agent was assigned based on the national category purchase cycle from Numerator data and that agent's probability of buying the brand, noting that those in the Movable Middle had a somewhat higher rate of category buying. (Source: 15 months of Numerator receipt scanning data.) (See Table 2.)
c) The probability of receiving an ad impression was based on the quantity of impressions delivered in a given week by each media channel, distributed across the 172 audiences based on media consumption patterns by audience as represented by the TransUnion (Neustar) system segment data. Then the impressions that went to a given audience were randomly assigned to corresponding individual agents. Our digital consumers could have received any number (including 0) ad impressions of a given channel, although we applied frequency capping rules for digital channels as it is typical industry practice to not have an ID receive more than a certain number of ad impressions in a given time period.
d) The response to advertising was governed by the logit function with effectiveness weights per media channel adjusted according to TransUnion (Neustar) MTA typically observed results. The advertising variable was in turn governed by imbedded functions that reflected the time decay of advertising impact,[43] a 'diminishing returns curve' that reflected the diminishing impact of each successive ad impression[44] to a given consumer, and an overall calibration to return a ROAS that was consistent with TransUnion norms.

Table 2: Heaviness of category buying versus loyalty among 2+ time buyers

Loyalty group	Index of category purchasing
Low Loyal	99
Movable Middle	107
High Loyal	80

The simulations were conducted to generate weekly buying over 52 weeks for each of the agents. We used a multi-level Monte Carlo simulation approach to simulate if:

1. An agent made a category purchase based on their assigned category purchase cycle.
2. An agent bought the brand of interest given a category purchase, based on their assigned probability of choosing the brand.
3. An agent received ad impressions that affected their probability of buying the brand as input into step 2.

Table 3: Comparing probability of purchase segments

Segment	% Category buyers	Defined by probability of brand choice that is . . .
High Loyals	2%	Over 80%
Movable Middle	16%	20–80%
Low Loyals	82%	Less than 20% (most are at or near 0)

The simulations were run multiple times for four main scenarios:

1. With no incremental advertising (to set a baseline for validating the agent rules and serve as an unexposed control for calculating ROAS).
2. A 'base' incremental media plan which was a starting point.
3. A 'reach'-improved plan, where the incremental advertising was reallocated across media channels to improve reach.
4. A targeting plan where we attempted to deliver as much advertising as possible to the Movable Middle to optimise the 'Outcome'. Based on TransUnion (Neustar) guidance, we assumed that 70 per cent of digital advertising could be targeted to this collection of audiences and that 25 per cent of linear television advertising could be targeted to the Movable Middle by making better programme choices.

We assumed no seasonality for clarity of interpretation.

From the Beta distribution fit to the brand, we calculated the size of segments as shown in Table 3.

We simulated a US$10 million incremental ad campaign, divided evenly over 8 weeks, being run starting at week 41 of a 52-week timeline. This campaign budget level was chosen to be reasonable in the context of the brand's annual ad spending level and also large enough that marketers reading this paper would not think we were cherry-picking only small and inconsequential increments. We then tested two media strategies for deploying these campaign funds; one plan was based on optimising for reach (no targeting other than category buyers); the other was a plan where targeting the Movable Middle was turned on by deploying nearly three times the media weight to the top quartile of TransUnion (Neustar) audiences in terms of the density of the Movable Middle. This resulted in an increase of ad impressions delivered to the Movable Middle from 16 per cent of ad impressions to 24 per cent of ad impressions. This degree of targeting was believed to be highly achievable.

The media plan allocations were, as shown in Figure 2, guided by marketer input and CPM (cost per thousand [impressions]) assumptions that were derived from a well-respected industry source (eMarketer).

SIMULATION RESULTS

First, as validation that our representation was tuned properly, we note that our agent-based model was able to replicate the brand's actual performance nearly perfectly, comparing the baseline simulation results to Numerator data, as shown in Table 4.

Note the significance of this validation of our agent-based representation of the brand as the model was fit to 172 segments and then recombined; also, penetration is not at all an input into the Beta distribution, so the penetration estimate was purely an emergent calculation.

Table 5 compares the reach plan and the targeting plan ROAS results.

As can be seen, the targeting plan delivered 50 per cent higher ROAS versus

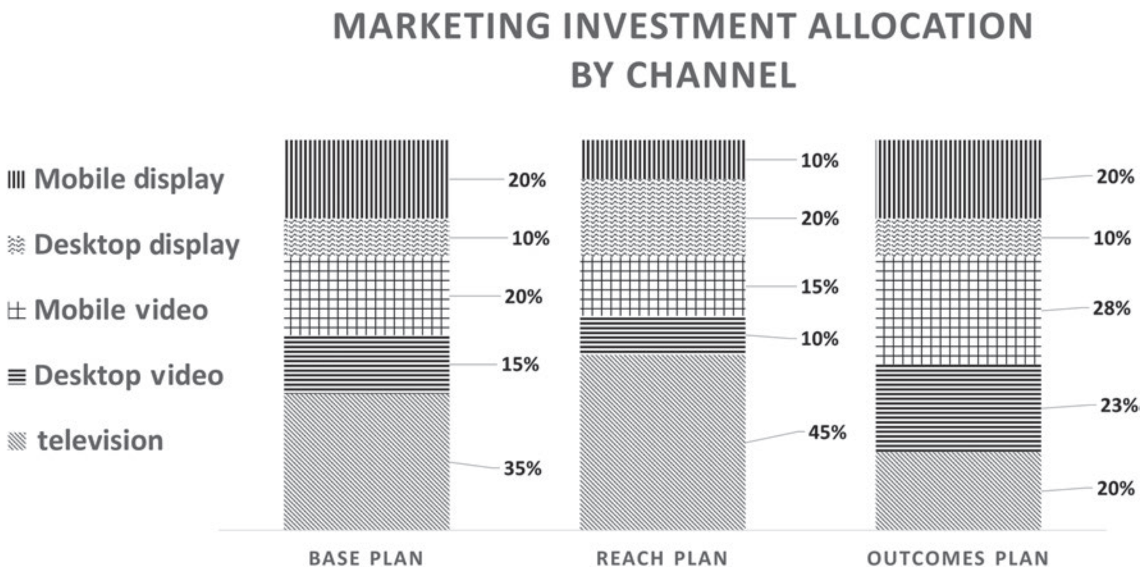

Figure 2: Allocation of incremental media plans investigated with Monte Carlo simulations
Source: eMarketer

Table 4: Comparing simulated and actual brand performance measures

Measure	Simulated data with no incremental advertising (scenario 1)	Numerator data
Market share (of purchase occasions)	10.3%	10.2%
Cumulative penetration (12-month)	25%	26.2%
Repeat rate	45%	44%

Table 5: Comparing reach and targeting plan ROAS ($US)

Marketing plan	Total revenue (weeks 41–52)	Incremental revenue (over baseline)	ROAS
Base plan	$101.5m	$21.8m	$2.18
Reach plan	$101.2m	$21.5m	$2.15
Targeting plan	$112.5m	$32.7m	$3.27

Return on ad spend (ROAS) is a common advertising productivity metric measuring the incremental revenue attributed to incremental ad spending. ROAS is calculated as the ratio of incremental revenue to incremental ad spending.

the reach plan. The reach plan was marginally worse than a typical (ie the base) plan.

The relationship in ROAS levels by segment for the base media plan conformed very closely to our theoretical calculations based on the logit function and the Beta distribution, as shown in Table 6.

Furthermore, the ROAS levels by each of the 172 audiences were also as expected in that there was a strong correlation between the density of Movable Middles and the ROAS from each audience. Figure 3 shows the relationship where the TransUnion audiences are arranged left to right, high to low ROAS.

Finally, we observed an unanticipated additional benefit of targeting audiences rich in the Movable Middle: this strategy also

Table 6: ROAS by probability of choice segment

Segment	ROAS from base plan
Low Loyals	$1.38
Movable Middle	$6.70
High Loyals	$1.84

delivered a 13 per cent higher conversion rate of non-buyers (defined on the first 40 weeks of simulated data) into buyers versus the reach plan (see Table 7). While there is a mathematical reason based on the differing shape of the Beta distribution where a brand has a large versus small share, this can also be interpreted as Low Unresponsives in audiences with high concentrations of Movable Middles, are more likely to be lookalikes for Movable Middles.

This suggests that targeting the Movable Middle might best serve a brand's needs for both short term ROAS and long-term growth.

EMPIRICAL EVIDENCE OF ROAS DIFFERENCES BY SEGMENT

The final step was to determine if our Monte Carlo simulations of ROAS as a function of probability of purchase reflected in-market experience.

Case study of an online financial services brand

In 2022, a study was devised with an online financial services brand guided by the MMA and analytics executed by the authors, including the TransUnion (Neustar) organisation. The online financial services brands' market share reflected the highly fragmented nature of financial services companies. The study was designed to be single source using the TransUnion OneID backbone matching to the survey company Dynata's panel. From this matching process, a backbone of over 600,000 IDs was created of IDs known to both TransUnion and Dynata. We tracked conversion behaviour

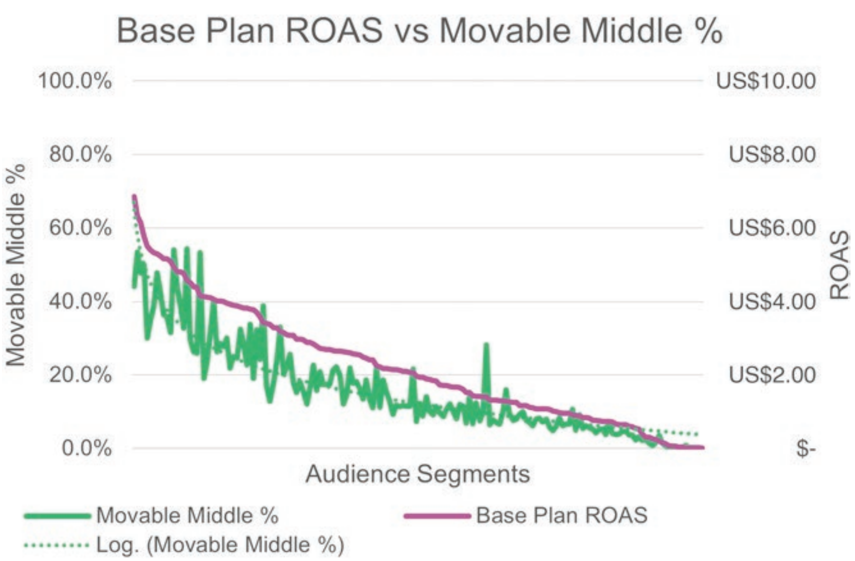

Figure 3: Base Plan ROAS compared with Movable Middle fraction for TransUnion segments ordered by decreasing ROAS
Source: TransUnion (Neustar) analysis

Table 7: Conversion rates of non-buyers by media plan

Buyer type	No extra media	Reach plan	Targeted plan
Non-buyers	3.9%	5.6%	6.3%

Table 8: Base and lifted conversion rates of Movable Middles to Non-Movable Middles

Segment	Conversion rate index: Not exposed to any heavy up tactic	Conversion rate index: Exposed to one or more heavy up tactics	Lift
Non-Movable Middles	100	117	17 (A)
Movable Middles	185	580	396 (B)
Lift Multiplier			23X (B/A)

(ie opening a new account) and ad serving for all IDs. In addition, we had survey results from 9,445 Dynata panelists, giving us single source data. The survey was used to classify IDs into the Movable Middle versus not Movable Middle using a constant sum question.[45] Any ID who gave between 2 and 8 (out of 10) points to the client brand was classified as the Movable Middle.

Using their current creative assets, the client increased media weight to 2–4 times their 'business as usual' spending levels, depending on channel, directed to the study backbone. We achieved an average of 40 per cent reach for each of the tactics (CTV, online video, display and social platforms). Unexposed IDs who were interviewed were balanced via raking to exposed IDs on prior customer status, age, gender and household income.

The campaign with heavy up media started in mid-April and ran until mid-June. We looked at conversion patterns through the end of June to allow for some carryover effects. Non-Movable Middles could have been either High Loyals or Low Loyals but as expected by Beta distribution patterns, well over 90 per cent had probabilities of choosing the client brand below 20 per cent and most were at 0 probability (no points to client brand). The results are shown in Table 8. We saw 23-times higher lift in response to ad exposure for the Movable Middle.

THE RELATIONSHIP OF PROBABILITY OF PURCHASE AND HEAVINESS OF BRAND BUYING

Because the Persuadables research finds systematic patterns of ROAS by heaviness of brand buying, it is important to understand the connection between the two frameworks and if the results are supportive of one another. Marketers with first party transactional data such as retailers can organically classify customers by heaviness of buying but do not know if they are in the Movable Middle as they do not know what those customers are buying from competitive brands. However, by surveying their customer segments[46] using constant sum questions or by analysis of receipt scanning data, a marketer can determine if the concentration of Movable Middles is higher than average among their own heavy or moderate buyers. In the case of the brand of frozen pizza, heavy and moderate buyers do, in fact, have very high concentrations of Movable Middles and non-brand buyers have an extremely low concentration from Numerator data (see Table 9).

The high concentration of Movable Middles among heavy buyers gives us a reason for why we observed high ROAS

Table 9: Movable Middle as a function of heaviness of brand-buying

	% of the segment that is in Movable Middle
Heavy buyers	75%
Moderate buyers	52%
Light buyers	28%
Brand average	16%
Non-buyers	2%

Buyers are defined as Heavy, Medium or Non-buyers as based on prior eight months of purchasing behaviour. All buyers are split equally into three groups.

levels for that buyer segment in the Persuadables study consistently across the three brand campaigns. This finding is supported by the reasonable assumption that heavy buyers of a brand tend to be heavier category buyers, considering more brands, and therefore more attentive to marketing communications that will help them choose what to buy.

CONCLUSION AND IMPLICATIONS

Conclusion

Returning to our original question, 'Are marketers targeting too much, not enough, or simply targeting the wrong consumers with their advertising?', we now have answers.

A more beneficial sales result from the same ad budget can be obtained by delivering extra media weight to any audience that has a significantly higher-than-average density of Movable Middles, funded by an offsetting reduction in spending against Non-Movable Middles.

Our findings were derived mathematically via our specific orchestration of mathematical models, then supported by in-market results, both our work and other published work. Collectively these works have found it is more productive to target marketing efforts to swing groups called Movable Middles, switchers, vulnerables, fence sitters, swing voters, etc.

While targeting the Movable Middle has been shown to produce 50 per cent greater ROAS, that might seem like a short-term strategy to some. However, this targeting plan also led to 13 per cent higher rates of conversion of non-buyers into buyers versus a media plan that is built for broad reach. The primary explanation is based on discovering that those with a near-0 baseline probability of buying the brand are the largest segment of category buyers and they are shown to have an extremely low likelihood to respond to a brand's advertising.

The broad applicability of targeting Movable Middles is also suggested by the range of applications across CPG, industrial products, financial services and catalogue buying with similar results.

Implications and discussion

Marketers should test these principles on their own business, and if validated, have confidence to include these targeting principles in their planning stages for an ad campaign.

In terms of practical use for media planning, marketers cannot target segments; they target audiences that exist or are built via lookalike modelling. Any audience warrants extra media weight if it offers a considerably higher than average concentration of Movable Middles. In this sense, we make no distinctions between digital addressable marketing, linear television, shopper marketing (one retailer or DMA [designated marketing area] versus another) etc. In other words, the Movable Middle targeting idea can and should be activated via a broad array of marketing channels.

Marketers should also pay attention to the multipliers of hyper-responsiveness of the Movable Middle towards their brands. While our maths for a 10 per cent share brand suggested that the Movable Middle would be five times more responsive to advertising, our financial services case study showed them to be even more hyper-responsive at 23X. We have also seen multipliers reported as low as 2X from Reckitt on a study conducted on Enfamil, reported by their CMO at an MMA conference (CEO/CMO summit, July 2022, Napa Valley, CA.) We also report on a CPG case study where the Movable Middle lift was 4–8 times (depending on the metric) versus Non-Movable Middle consumers. The maths implies that this range in outcomes can be anticipated by the shape of the Beta function based on the share and repeat rate for each particular brand.

LIMITATIONS AND AREAS FOR FUTURE STUDY

The authors note that the theory was created with data on frequently purchased CPG products, but we encourage marketers in all sectors to verify these results on their own brands. We also encourage those with first party data assets to test targeting their paid media towards heavy and moderate buyers with extra media weight if they are proven to deliver high concentrations of Movable Middles.

Our research did not test the relative benefit of targeting consumers who are thought to have the greatest lifetime value.[47] We would welcome research to examine if this additional criterion adds value *vis-à-vis* the Movable Middle target segment.

Our analysis assumed average creative quality. We believe the multiplier applies regardless of creative. However, if the creative is superior, the multiplier will operate against a higher potential for lift, resulting in truly superior results. This principle should be tested by marketers on their own brands.

We did not address the potential effect of advertising on quantity bought or what is often called 'buying rates'. It is possible that a lift in buying rates would increase response to advertising among Movable Middles and High Loyals which can only be determined empirically from a series of case studies.

Finally, note that we implemented assumptions of stationarity so that this analysis is intended to apply to relatively stable mature brands, in stable markets and categories, seeking greater return on their ad spending. There is evidence[48] that smaller brands' marketing activities might have cumulative effects that extend the short-term benefits of advertising and promotion. Also, we note that the new brand will only be able to follow our targeting recommendations once it has formed its own Movable Middle.

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