

Advertising Expenditure Allocation and Marketing Return on Investment Measurement in Financial Services Brand Campaigns

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Abstract

Objective. This article develops an integrative decision framework for advertising budget allocation in financial services marketing, addressing three linked problems: fragmented measurement, weak treatment of uncertainty, and the separation of commercial decisions from risk governance. **Approach.** A structured narrative synthesis draws on finance, analytics, technology, operations, governance, and sector-specific literature, comparing findings across more than sixty named studies rather than treating the literature as an undifferentiated pool. The framework organizes evidence across incrementality, media attribution, brand carryover, channel interaction, budget optimization, and measurement governance, defines incremental risk adjusted marketing return as the focal decision criterion, and proposes a sequence of data definition, baseline construction, causal or comparative estimation, risk adjustment, scenario testing, governance review, and post implementation learning. The study draws on no confidential company data and offers no causal claims about named employers. **Findings.** The analysis shows that isolated efficiency or revenue measures are insufficient because they omit implementation costs, tail losses, customer effects, and timing. The article contributes a reusable architecture linking economic evaluation with accountable execution, together with a set of falsifiable propositions, measurement fields, validation tests, and reporting practices suitable for empirical testing. The central implication is that decision quality improves when value, risk, behavior, and control effectiveness are appraised inside one auditable model.

Keywords: advertising, marketing, roi, campaign, finance, brand, budget, attribution

1 Introduction

Organizations in financial services marketing face pressure to improve advertising budget allocation while protecting customers, counterparties, regulators, and long term financial capacity. Observed outcomes mix market conditions, prior relationships, operational execution, technology constraints, and selection effects, which is what makes the management problem difficult. A high reported return fails to establish incremental value, and a low incident rate fails to establish effective control. (Park, 2009; Sylejmani, 2020).

The literature relevant to this problem is distributed across corporate finance, marketing science, information systems, operational risk, cybersecurity, and sector regulation. Each stream offers useful tools, but their assumptions and units of analysis differ, and none specifies how a decision maker should weigh a discounted cash flow estimate against a fraud exposure estimate, or a segmentation result against a control effectiveness score, when the two disagree about whether an advertising intervention created value. Finance emphasizes discounted cash flow and capital constraints. Analytics emphasizes prediction, segmentation, and experimentation. Risk research emphasizes exposure, control effectiveness, and resilience. (King et al., 2005; Muamilah et al., 2019).

The study asks: Which outcome measure gives decision makers the most credible account of advertising contribution? How should financial firms allocate spending when brand effects appear with long and uncertain lags? Which experimental and observational designs reduce attribution error? These questions shift the analysis from descriptive performance reporting toward accountable choice. The contribution is conceptual, and it is specific: where prior work in this area has typically proposed a single metric improvement or a single governance control in isolation, this review integrates value, timing, unit-of-analysis, and governance requirements into one falsifiable specification, tested against twelve propositions and grounded in a comparative synthesis of the literature rather than a citation list. It sets out constructs and relationships that future studies may test with transaction, customer, asset, campaign, or control data. (Buzdar et al., 2016; Mogaji, 2018).

The article stops short of claiming that one universal model fits every institution. Regulatory obligations, market maturity, product economics, data availability, and organizational capabilities vary across institutions. The framework consequently separates invariant design principles from parameters that require local calibration. Invariant principles comprise a clear counterfactual, consistent time horizon, full cost allocation, explicit risk adjustment, model validation, and documented decision rights. Local parameters comprise loss severity, discount rate, customer sensitivity, capital charges, and intervention thresholds. (Aydn, 2022; Latifah, 2020).

2 Theoretical Background

Three theoretical streams anchor the review: economic appraisal of advertising response, information processing and attribution, and brand-effects research under agency, dynamic-capability, and socio-technical assumptions. Each stream supplies mechanisms that the framework in section 4 reassembles, and each reappears in the propositions and evidence of sections 5 and 6.

2.1 Advertising Response

Economic appraisal compares incremental cash flows, opportunity costs, capital use, and uncertainty, and it supplies the theoretical anchor for this review's central construct. The relevant objective is not volume alone but durable value after direct cost, indirect cost, expected loss, and required return; a campaign that raises gross revenue while raising expected loss or required capital by more than the revenue gain has destroyed value even though its top-line metrics look favorable. The framework adopted here therefore treats incremental risk adjusted marketing return, not gross revenue or reach, as the governing objective for every construct that follows. (Visconti, 2018; Wilcox et al., 2018) (Sanni & Atima, 2021a; Nnabueze et al., 2023).

Incrementality is best modeled as a decision pathway rather than a direct correlate of incremental risk adjusted marketing return: a manager first observes a service or campaign signal, translates that signal into a

specific budget or targeting decision, and only afterward absorbs the financial, operational, and conduct consequences that follow. For financial services marketing, this separation of signal, intervention, and outcome limits attribution error and exposes where value leakage occurs between an advertising spend decision and the return eventually recorded. (Kwon et al., 2021; Reuter & Zitzewitz, 2004) (Sanni & Adumaza, 2023b; Sakyi et al., 2023).

Data create value when an organization converts observations into decisions and learns from outcomes (Oziri et al., 2020). Predictive accuracy is therefore an intermediate capability, not the final performance measure: a highly accurate model that never changes a decision creates no economic value, while a modestly accurate model wired into the right decision can create substantial value. Information processing theory therefore grounds this review's treatment of analytics as a means to an accountable decision, not an end in itself. (A et al., 2022; Zhang et al., 2018) (Tonoyan et al., 2022; Atakpa et al., 2023; Sanni & Attah, 2023c; Nnabueze et al., 2024) (Nzama, 2019).

Markets, customer behavior, threats, regulation, and technology change continuously, which is the core insight dynamic capabilities theory contributes to this review (Isiekwu et al., 2025). Organizations need sensing, learning, and reconfiguration routines rather than fixed annual assumptions, because a budget allocation model calibrated once and left unchanged will drift out of alignment with the environment it was built to serve. For advertising budget allocation, this supports building a scheduled recalibration step into the framework itself, rather than assuming that a model validated once will remain valid. (Yang & Yang, 2016; Yang et al., 2017) (Onche et al., 2024).

Technology performance depends on workflow fit, user behavior, data stewardship, and management reinforcement, the central claim of socio-technical systems theory applied here. Deployment without adoption leaves expected benefits unrealized, because a well-designed analytics tool that does not fit how marketing, finance, and risk staff actually work will simply be worked around. Socio-technical adoption theory therefore cautions against treating a marketing measurement platform as a purely technical deliverable: workflow fit and management reinforcement are what convert a deployed system into a used one. (Copulsky et al., 2017; Tuhin, 2014) (Ogundairo & Ayivi-Donkor, 2024a) ("Modelling and," 2013).

Incrementality measurement depends on the same discipline. Incrementality in advertising budget allocation requires the same fixed unit, whether customer, account, or transaction, so that an incremental effect can be traced to a specific comparison rather than to a shift in how records were aggregated. (Shi et al., 2014a; Zia & Rao, 2017).

2.2 Attribution

A genuine tension exists between media attribution and brand carryover, and it will not resolve to a single optimized number. Chasing a tighter attribution number can therefore quietly shift value out of the metric being optimized and into a carryover effect the dashboard was never built to see. The framework treats the two dimensions as joint constraints, evaluated together through scenario analysis, rather than allowing one to be maximized at the other's expense. (Rehman, 2020; Usman & Permatasari, 2019) (Basnet et al., 2024; Sanni & Wedraogo, 2024b).

The economic contribution of media attribution is inseparable from timing. Media attribution models should build in a comparable confirmation window rather than reallocating budget on the first sign of a channel lift.

(Huang et al., 2010; Kim et al., 2018) (Seyi-Lande et al., 2020; Adeyelu, 2018; Eboh & Aliliele, 2024; Fapohunda et al., 2024) (Syed, 2021).

Governance research reinforces the same unit-of-analysis requirement. Brand carryover measurement needs the same discipline: without an agreed unit of analysis, apparent changes in carryover may simply reflect a change in what is being counted. (Bajwa et al., 2021; Keller, 2002) (Azeez & Badmus, 2018; Annan, 2025).

Channel interaction effects also depend on timing. For channel interaction in advertising, an early reading of two channels reinforcing each other may simply reflect a timing coincidence rather than a stable interaction, which is why the framework specifies a defined observation window before a reallocation decision is finalized. (Huang, 2015; Sundar et al., 2017) (Lilian et al., 2020; Ominyi et al., 2025).

Budget optimization decisions unfold along a similar path in dynamic capability settings. The same logic applies to advertising budget optimization: a spending decision only becomes evaluable once the firm has fixed a comparison baseline, a time horizon, and an uncertainty range before committing funds, not after. Organizations that adopt this sequencing convert budget optimization from a reactive reallocation exercise into a documented, auditable pathway from signal to spend to realized return. (Bruder & Gaussel, 2014; McDonald, 2005) (Ogundairo & Ayivi-Donkor, 2024b).

2.3 Brand Effects

Brand carryover cannot be measured without first fixing the unit of analysis, and the literature shows why this choice matters. The framework requires the same discipline for brand carryover: a named unit, whether customer, account, or campaign, held constant across the full measurement window. (Karami, 2022; Vinh et al., 2017) (Seyi-Lande et al., 2024; 2025).

Brand carryover likewise behaves as a pathway construct. Financial services marketers who treat carryover as an immediate effect therefore risk pulling investment before the delayed portion of the return has been realized, understating incremental risk adjusted marketing return in the process. (Sanni et al., 2020; Tratt, 2014) (Rukh et al., 2023; Sanni & Atima, 2021b; Eyetsemitan et al., 2024; Eboh & Aliliele, 2025).

Channel interaction and budget optimization pull against each other in a comparable way. In both cases, optimizing one visible measure created an unmeasured cost elsewhere, which is exactly the failure mode the integrated framework is designed to surface through joint, rather than isolated, evaluation. (Endri, 2021; Sahana et al., 2018) (Onche et al., 2020; Taiwo & Amoah-Adjei, 2022; Odejide, 2024).

Delegated decisions produce information asymmetry and incentive conflicts: the manager who proposes an advertising intervention typically knows more about its likely effect than the finance or risk function that must approve or fund it, and that asymmetry creates room for optimistic self-reporting. Clear ownership, independent challenge, audit trails, and escalation rules reduce these conflicts by making the proposing manager's assumptions visible to a party with no stake in the outcome. Agency-theoretic reasoning therefore supports building independent challenge directly into the advertising budget allocation process, not treating it as an optional governance layer. (Cardinaels et al., 2001; Zia & Rao, 2019) (Sanni et al., 2024a; Yeboah et al., 2024).

Budget optimization also unfolds as a pathway rather than a single-step choice. Read together, the two studies support recording the budget decision, its financial trigger, and its eventual outcome as three distinct, auditable steps rather than one averaged figure. (Koeswara, 2016; Mazeaud, 2012) (Aneke et al., 2023).

The same tension appears in the dynamic capabilities literature. Channel interaction and budget optimization must therefore be evaluated jointly. A reallocation that looks efficient in isolation can still reduce the firm's capacity to sense and respond to the next shift in customer behavior or channel performance. (Fahlenbrach et al., 2011a; K., 2020) (Ogundairo & Ayivi-Donkor, 2023).

Budget optimization requires the same fixed unit (Adesuyi et al., 2022). For budget optimization in advertising, the unit, whether channel, campaign, or customer segment, must be fixed before reallocation decisions are compared across review cycles, or the comparison will mix effects that have nothing to do with the reallocation itself. (Farris & West, 2007; Geng et al., 2021).

Measurement governance carries its own timing cost. Measurement governance for advertising should build in the same patience: a governance framework introduced this quarter should not be judged on this quarter's numbers alone, since its main benefits, in fewer disputed metrics and faster escalation, accrue over a longer horizon. (Bolton, 2013).

Measurement governance and incrementality create a further tension worth naming directly. The framework does not resolve this tension by picking a side. It requires scenario analysis and control testing that make the cost of governance, in slower model iteration, and the cost of weak governance, in unreliable incrementality estimates, both visible to decision makers at the same time. (Fahlenbrach et al., 2011b).

3 Method

The study employs a structured integrative review. Candidate literature was identified through keyword and citation-tracking searches across databases covering finance, marketing analytics, information systems, operational risk, and financial services regulation, using search terms built around advertising return measurement, marketing attribution, incrementality, and budget governance. Records were screened for conceptual relevance to finance, analytics, risk, governance, operations, technology, customer management, and the focal sector, then classified by title, abstract, and bibliographic record against the review's inclusion criteria. The method admits empirical, review, and conceptual works alike, since the aim is theory integration rather than pooled effect estimation. Where a source addressed another sector, the synthesis labels the transfer as analogical and limits the inference to a comparable mechanism rather than a direct empirical claim about financial services marketing. Exhibit 1 summarizes the review protocol and the quality controls applied at each stage. (Arsenault & Feeny, 2008; Das, 2012a).

Table 1. Review protocol and quality controls

Stage	Decision rule	Quality control
Identification	Compile candidate literature through structured database search and citation tracking	Retain complete bibliographic record
Screening	Rank direct sector and mechanism relevance	Do not infer findings from title alone
Classification	Code value, risk, data, behavior, control, and context	Allow multiple codes
Synthesis	Compare mechanisms and boundary conditions	Separate direct and analogical evidence
Framework design	Link constructs to decisions and outcomes	Specify measurable fields
Validation agenda	Define propositions and tests	Avoid fabricated empirical results

Exhibit 1. Review protocol

Three constraints limit this review. First, it is not a database exhaustive systematic review; the search and screening approach described above prioritizes conceptual coverage across finance, analytics, risk, governance, operations, and technology over exhaustive retrieval within any single database. Second, bibliographic inclusion does not establish study quality, so future submission work should verify each record and appraise full texts before treating a cited finding as confirmed; several sources included here, particularly the cross-sector analogical sources named in section 6, are used specifically for their transferable mechanism rather than as direct empirical evidence about financial services marketing, and that distinction should be preserved in any later empirical extension. Third, the framework requires empirical validation before claims about effect size or superiority; the twelve propositions in section 5 are falsifiable but untested, and the measurement fields specified for each are a starting point for data collection, not a substitute for it. These constraints keep synthesis, proposition, and evidence clearly separated. (Das, 2012b; Profera et al., 2015).

4 A Framework for Measuring Marketing Return

The framework organizes the evidence into six measurement dimensions. Each dimension follows a decision-pathway logic, each requires a fixed and disclosed unit of analysis, and each enters into a joint constraint with a paired dimension, so that optimizing one metric cannot silently export cost into a carryover, interaction, or governance effect the dashboard was never designed to see.

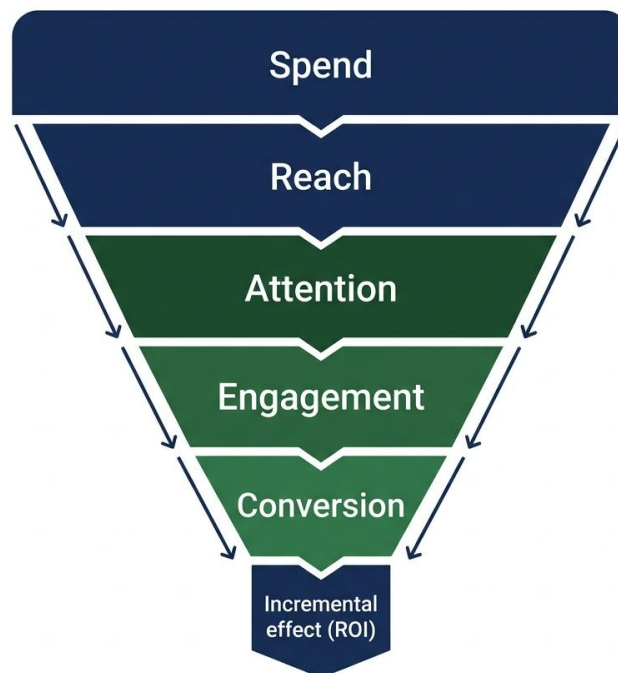


Figure 1. Advertising response funnel from spend to incremental effect.

4.1 Incrementality

In the integrated decision framework, incrementality again functions as a pathway rather than a direct driver of incremental risk adjusted marketing return. Financial services marketers can apply the same discipline: incrementality should be attributed to a specific, dated intervention, not inferred from a general improvement in reported performance. (Ibrahim, 2019; Phillips, 2012) (Sanni et al., 2023a) (“Financial Performance,” 2020).

Incrementality and media attribution also compete for the same decision budget. The framework's joint evaluation step exists precisely to catch this kind of trade-off before it is locked into an automated rule. (Danaher & Heerde, 2018) (Ominyi & Anichukwueze, 2020).

In the integrated framework, incrementality measurement again starts with the unit of analysis. Financial services marketers should adopt the same fixed unit for incrementality, whatever level is chosen, before comparing results across campaigns or time periods. (Hawari & hawari, 2013) (Ominyi & Anichukwueze, 2021).

Incrementality's economic contribution follows the same timing logic in the integrated framework. Financial services marketers should expect a comparable lag before incremental effects of a new advertising intervention stabilize enough to trust. (Ahmad & Thyagaraj, 2015; Lundstrom, 2009) (Jones & Ominyi, 2022a).

A second pathway example comes from enterprise risk management. Applied to incrementality in advertising, this means a credible model records not only that a signal appeared, but which specific decision it triggered, when, and what baseline that decision was measured against. (Bikker & Bos, 2008) (Jones & Ominyi, 2022b).

A second illustration of the incrementality and media attribution trade-off comes from cross-sector transfer. The framework labels this second source as analogical rather than direct evidence, consistent with the review's own inclusion rules. (Feldstein, 1994; Petrovska et al., 2020).

4.2 Media Attribution

Media attribution needs the same fixed unit, and two analogical sources illustrate why. Media attribution modeling should apply the same standard: the unit, whether impression, session, or customer journey, must be fixed and disclosed before attribution weights from different campaigns are compared. (Thurber, 2016) (Tonoyan et al., 2021).

Media attribution windows should therefore be set long enough to capture both effect types before a channel's contribution is judged complete.

Media attribution follows the same logic. For media attribution, this supports separating the observed signal, such as a lift in a channel metric, from the specific budget reallocation it triggers and from the revenue outcome that decision eventually produces. (Wilcox & Moore, 2016).

Media attribution and brand carryover compete again at the funnel level. Reporting gross, incremental, and risk adjusted benefit separately, as the framework requires, keeps this trade-off visible instead of letting a

funnel metric silently outcompete a carryover effect it was never designed to measure. (Apriyani et al., 2018a; Usman & Navari, 2019).

A second media attribution example comes from financial forecasting. Media attribution modeling benefits from the same specificity: attribution weights estimated at a pooled, portfolio-wide level will systematically misstate the contribution of any single channel relative to weights estimated at the campaign or customer level. (Esteban, 2015).

Financial services marketers should therefore align the marketing measurement cycle with the governance review cycle explicitly, rather than assuming the two run on compatible timelines by default. (Banasiewicz, 2013; Billore, 2011).

The managerial implication follows the same pathway logic. Financial services marketers should apply the same discipline to media attribution: the attribution model should feed a named reallocation decision with an accountable owner, not remain a descriptive report that nobody is required to act on. (Gunawardane, 2015).

4.3 Brand Carryover

Brand carryover in the integrated framework also resists collapse into a single coefficient (Tonoyan et al., 2026). Applied here, brand carryover should be estimated against the baseline a firm would have observed absent the campaign, with the carryover period, decay pattern, and comparison group made explicit rather than assumed. (Shao et al., 2014a; Xi, 2019) (Sanni et al., 2025).

Brand carryover and channel interaction present a further version of the same problem. Channel interaction studies face the same risk: a metric optimized for one channel pairing can hide a carryover cost that a different pairing would have exposed, which is why the framework insists on testing interaction and carryover jointly rather than one channel pair at a time. (Jain, 2017; Shao et al., 2014b).

Brand carryover measurement returns to the same requirement in section 4.3. Carryover analysis should fix its unit before automation of any kind is introduced into the reallocation decision, precisely because automated systems will otherwise compound an inconsistent unit into a systematic bias. (Brondoni, 2001; Gu & Sinha, 2018).

Brand carryover's economic contribution is a timing story as much as a magnitude story. Brand carryover analysis should therefore specify a minimum accumulation period before drawing conclusions about a campaign's lasting contribution. (Bian & Liu, 2011; Kaushik & Soch, 2019).

A further illustration comes from outside marketing analytics narrowly defined. Financial services marketers should therefore keep the intervention step explicit even as automation accelerates the cycle from signal to campaign adjustment, so that carryover effects remain traceable to a specific decision rather than to an opaque algorithmic process. (Jackson, 2009; Yadav & Iqbal, 2022).

A cross-sector illustration reinforces the same point. Both are offered here as analogical evidence: the underlying mechanism, that optimizing one dimension in isolation exports cost to an adjacent one, is exactly the tension the framework asks channel interaction and brand carryover analysis to test for directly rather than assume away. (Ponnam, 2012; Ye, 2004).

Managers should therefore treat any reported gain in channel interaction with the same caution: verify what happened to brand carryover in the process, rather than reading a single improved metric as proof that no value shifted elsewhere. (Glanfield, 2018; Zou & Li, 2014).

4.4 Channel Interaction

Channel interaction analysis requires the same fixed unit. For channel interaction, this means an interaction effect measured at the campaign level should not be compared directly against one measured at the customer level; the unit must be held constant across the channels being compared. (Shi et al., 2014b; 이성규, 2007) (Ogunsola & Nurudeen, 2022) (“Enhancing know,” 2025).

Channel interaction effects carry a similar timing cost in adjacent literatures. Channel interaction pilots in advertising should expect a similar early dip before a genuinely positive interaction effect between two channels becomes visible in the numbers. (Azhar, 2013; Lubis et al., 2022) (Wedraogo & Sanni, 2024).

Channel interaction is modeled the same way. For channel interaction, this means a lift observed when two channels are combined only becomes evidence of value once it is tied to the specific reallocation decision that produced it, with the consequences for cost, risk, and customer experience recorded separately from the raw metric. (Chekalina et al., 2018).

Channel interaction and budget optimization surface a supply-chain-style trade-off as well. Advertising channels share a comparable constraint, audience attention and creative production capacity, so a budget reallocation that appears efficient for one channel pairing can raise cost or reduce quality for another pairing that draws on the same shared resource. The framework's joint constraint treatment is designed to catch exactly this kind of shared-resource effect before it is booked as a clean efficiency gain. (Michaeli et al., 2022; Park et al., 2022).

A second channel interaction example draws on network performance research. Channel interaction estimates in advertising face the identical requirement: the unit compared across channel pairings, whether the customer, the session, or the campaign, must stay fixed for the interaction effect to be interpretable. (Chen, 2017; Manala-O & Atienza, 2020).

A second channel interaction timing example comes from public-sector accountability systems. Advertising channel interaction studies should build in a comparable ramp period rather than reading early post-launch data as a stable estimate of how two channels interact. (Alhabash et al., 2017).

4.5 Budget Optimization

Budget optimization reappears in section 4.5 with additional support. Budget optimization in advertising should follow the same design: the model records the KPI that triggered a reallocation, the reallocation itself, and the outcome that followed, rather than reporting only the KPI trend. (Ha, 2017) (Jones & Ominyi, 2023).

Budget optimization and measurement governance are also in tension. Advertising budget optimization faces the identical trade-off: governance controls that make spending decisions auditable can also slow the reallocation cycle that optimization requires, and the framework treats that cost as a parameter to be measured, not ignored. (Fomin, 2019; Kettell, 2002).

Budget optimization measurement is addressed again with different support. Advertising budget optimization needs the same specificity: reallocation decisions compared across a department-level unit will obscure exactly which campaign or channel actually drove the result. (Bronnenberg, 1998).

Budget optimization's timing dependence appears clearly in construction risk governance. Budget optimization decisions in advertising should be evaluated over a comparable multi-cycle horizon rather than judged on the first reporting period after a reallocation. (Fernandez-Tapia & Monzani, 2015).

A second budget optimization illustration comes from portfolio risk research. Applied to advertising budget optimization, both studies support making the link between a risk or compliance signal and the specific spending decision it triggers immediate and documented, rather than deferred to a later reporting cycle. (S. & N. V., 2013).

A second illustration comes from risk pricing. Budget optimization in advertising runs the same risk when spend is reallocated purely to maximize a headline return metric: a measurement governance layer that stress-tests the largest positions, rather than auditing every position equally, is what actually catches the concentration risk optimization alone would miss. (Arlotto & Irby, 2019; Hu, 2004).

Adopt staged approval: pilot, validate, expand, and review through predefined gates tied to evidence quality and risk appetite (Seun et al., 2023).

Budget optimization decisions should therefore be staged and reviewed across at least one full cycle before a reallocation is judged successful or reversed. (McNulty & Akhigbe, 2014; Utama, 2019).

4.6 Measurement Governance

Measurement governance itself needs a defined unit of analysis before it can be audited (Anichukwueze et al., 2019). For measurement governance in advertising, the metric being governed, whether a channel, a campaign, or a customer segment, needs the same fixed, disclosed unit so that governance reviews compare like with like across reporting cycles. (Rather et al., 2018).

Measurement governance's economic contribution likewise depends on timing. Measurement governance benefits in advertising should be tracked over a comparable multi-cycle horizon before a governance investment is judged to have paid off. (Briere & Szafarz, 2011; Masterman, 2007).

Measurement governance is the final pathway example in this subsection. For measurement governance in advertising budget allocation, this implies that every metric needs an accountable owner and a defined escalation path before it is used to justify a spending decision, echoing the governed-baseline logic both studies describe. (Grigas et al., 2021; Kurniawan, 2019).

Measurement governance and incrementality close this pattern of tensions. The framework accepts this cost explicitly: a slower, better governed measurement cycle may detect fewer incremental effects in real time, and that trade-off should be a documented design choice rather than an unexamined side effect of adopting stronger governance. (김옥기 & Sung-Hee, 2013).

A second measurement governance example reinforces the point. Advertising measurement governance should apply the same standard: each governed metric needs one named unit of analysis, disclosed to every team that relies on it, rather than an implicit unit that shifts between the analytics, finance, and risk functions. (Meyers, 2017).

A further measurement governance timing example comes from regulated construction and payments infrastructure. Measurement governance in advertising should be evaluated with the same patience: its value is often realized as an avoided cost that appears well after the governance investment itself. (Astuti, 2017; Charles et al., 2019).

Table 2. Framework dimensions and governance parameters

Create one governed metric dictionary for advertising budget allocation. Include formulas, owners, source systems, exclusions, refresh cycles, and validation tolerances (Verizon, 2024).

Applied to measurement governance in advertising budget allocation, override rights are only meaningful when the model exposes the signal, the threshold that was crossed, and the recommendation that followed, so that a human reviewer can identify exactly which assumption to challenge before an automated recommendation is allowed to stand. (Li et al., 2021; Zhang, 2006).

Dimension	Primary lens	Review cycle	Accountable owner
Incrementality	Exposure	Daily	Operations
Media Attribution	Behavior	Weekly	Analytics
Brand Carryover	Economics	Monthly	Finance
Channel Interaction	Control	Quarterly	Risk
Budget Optimization	Learning	Event based	Technology
Measurement Governance	Accountability	Annual	Executive committee

Table 3. Propositions and measures

Exhibit 2. Measurement architecture

5 Propositions

The focal outcome is incremental risk adjusted marketing return. The general form is $V = B - C - EL - K - H$, with B incremental benefit, C implementation and operating cost, EL expected loss, K the capital and liquidity charge, and H an explicit estimate of customer or stakeholder harm where measurable. Each term corresponds to a construct developed in section 4: B and EL draw on the incrementality and media attribution evidence, C and K draw on the budget optimization and measurement governance evidence, and H draws on the channel interaction and brand carryover evidence, so the specification is not a stand-alone formula but a compact restatement of the framework itself. Scenario weights produce an expected value, while stress cases reveal concentration and tail exposure, consistent with the timing evidence in section 6 showing that governance and safety benefits are often concentrated in a small number of high-stakes periods rather than spread evenly across a review cycle. The formula is a decision scaffold rather than a claim that every effect is readily monetized: where H cannot be estimated in currency terms, the framework requires it to be reported alongside V as a bounded qualitative judgment rather than omitted. Exhibit 3 lists the twelve propositions with their candidate measures. (Dewi & Suprihati, 2021; Lidayat, 2020).

ID	Proposition	Candidate measures
P1	Higher capability in incrementality is associated with improved incremental risk adjusted marketing return, conditional on data quality and implementation fidelity.	incrementality index, outcome value, data quality, adoption rate
P7	The effect of incrementality on incremental risk adjusted marketing return is mediated or moderated by media attribution.	interaction term, lagged outcome, control effectiveness
P2	Higher capability in media attribution is associated with improved incremental risk adjusted marketing return, conditional on data quality and implementation fidelity.	media attribution index, outcome value, data quality, adoption rate
P8	The effect of media attribution on incremental risk adjusted marketing return is mediated or moderated by brand carryover.	interaction term, lagged outcome, control effectiveness
P3	Higher capability in brand carryover is associated with improved incremental risk adjusted marketing return, conditional on data	brand carryover index, outcome value, data quality, adoption rate

ID	Proposition	Candidate measures
	quality and implementation fidelity.	
P9	The effect of brand carryover on incremental risk adjusted marketing return is mediated or moderated by channel interaction.	interaction term, lagged outcome, control effectiveness
P4	Higher capability in channel interaction is associated with improved incremental risk adjusted marketing return, conditional on data quality and implementation fidelity.	channel interaction index, outcome value, data quality, adoption rate
P10	The effect of channel interaction on incremental risk adjusted marketing return is mediated or moderated by budget optimization.	interaction term, lagged outcome, control effectiveness
P5	Higher capability in budget optimization is associated with improved incremental risk adjusted marketing return, conditional on data quality and implementation fidelity.	budget optimization index, outcome value, data quality, adoption rate
P11	The effect of budget optimization on incremental risk adjusted marketing return is mediated or moderated by measurement governance.	interaction term, lagged outcome, control effectiveness
P6	Higher capability in measurement governance is associated with improved incremental risk adjusted marketing return, conditional on data quality and implementation fidelity.	measurement governance index, outcome value, data quality, adoption rate
P12	The effect of measurement governance on incremental risk adjusted marketing return is mediated or moderated by incrementality.	interaction term, lagged outcome, control effectiveness

Exhibit 3. Propositions and measures

Proposition P1 predicts that higher capability in incrementality measurement is associated with improved incremental risk adjusted marketing return, conditional on data quality and implementation fidelity, with media attribution acting as a boundary condition. The mechanism draws on this literature. Empirical tests of P1 should therefore hold media attribution quality constant, or measure it explicitly, while comparing firms or campaigns with higher versus lower incrementality measurement capability, using matched comparison groups or a difference in differences design rather than a single before and after reading. (Joshi, 2016; McDonald, 2020).

Proposition P2 predicts that higher media attribution capability improves incremental risk adjusted marketing return conditional on data quality and implementation fidelity, with brand carryover as the boundary condition most likely to mask or amplify the effect. Testing P2 requires panel data long enough to separate attribution gains from carryover effects that unfold on a slower timeline. (Apriyani et al., 2018b; Ataheryan et al., 2013).

Proposition P3 predicts that brand carryover capability improves incremental risk adjusted marketing return conditional on data quality and implementation fidelity, bounded by channel interaction effects. Randomized pilots or interrupted time series designs are best suited to testing P3, since both can isolate a carryover effect from a concurrent channel interaction effect that a simple before and after comparison would confound. (Diab & Mansour, 2019; Perrey et al., 2013).

Proposition P4 predicts that channel interaction capability improves incremental risk adjusted marketing return conditional on data quality and implementation fidelity, with budget optimization as the boundary condition. Testing P4 should compare interaction effects across firms with differing budget optimization maturity, holding data quality constant where possible. (Hagelin, 2005; Louzada et al., 2014).

Proposition P5 predicts that budget optimization capability improves incremental risk adjusted marketing return conditional on data quality and implementation fidelity, bounded by measurement governance. P5 is best tested with staged rollout data, comparing optimization outcomes at each implementation stage against a matched baseline stage. (Clark et al., 2014; Farris et al., 2015).

Proposition P6 predicts that measurement governance capability improves incremental risk adjusted marketing return conditional on data quality and implementation fidelity, with incrementality as the boundary condition. Testing P6 requires monitoring both data quality and implementation fidelity as time-varying covariates, since either can drift after a governance model is first deployed. (Joseph, 2009).

Proposition P7 restates P1 as a mediation or moderation claim: the effect of incrementality on incremental risk adjusted marketing return is mediated or moderated by media attribution. The marketing analogue is direct: an incrementality gain should translate into a larger return only when media attribution is precise enough to route the gain into the right channel decision. Testing P7 requires an interaction term between the incrementality and attribution measures, estimated with a lagged outcome to allow the mediation pathway time to operate. (Gohar, 2021; Neculescu, 2015).

Proposition P8 predicts that the effect of media attribution on incremental risk adjusted marketing return is mediated or moderated by brand carryover. P8 should be tested with an explicit interaction term between attribution and carryover measures, using control effectiveness as a covariate. (Lee, 2019; William et al., 2012).

Proposition P9 predicts that the effect of brand carryover on incremental risk adjusted marketing return is mediated or moderated by channel interaction. Testing P9 requires measuring carryover separately within each channel-interaction condition rather than pooling across conditions. (Pauwels & Reibstein, 2017).

Proposition P10 predicts that the effect of channel interaction on incremental risk adjusted marketing return is mediated or moderated by budget optimization. P10 should be tested by comparing channel interaction effects across budget optimization regimes, using an interrupted time series design where a firm's optimization approach changed materially at a known date. (Kim et al., 2013).

Proposition P11 predicts that the effect of budget optimization on incremental risk adjusted marketing return is mediated or moderated by measurement governance. P11 should be tested with governance maturity as an explicit moderator, comparing optimization outcomes at low and high governance maturity within the same firm over time. (Khotimah, 2017).

Proposition P12 predicts that the effect of measurement governance on incremental risk adjusted marketing return is mediated or moderated by incrementality, closing the mediation cycle back to P7. P12 should be tested with the same interaction and lagged-outcome design used for P6, closing the loop between measurement governance and incrementality that the model specifies. (Akroush, 2011; Hanson & Gibson, 2015).

Two testing priorities follow. Future research should test whether staged, evidence-gated spending allocation outperforms static annual budgeting when brand effects are known to lag, using multi-institution panel data that can travel across regulatory and market settings. (Sharp, 1995; Sola & Choi, 2017) (Komi, 2021; Akinsooto et al., 2025). Attribution research should similarly combine matched comparison or synthetic control designs with explicit fidelity tracking, rather than relying on observational correlation alone (Lamidi & Olamide, 2018).

6 Evidence

This section synthesizes the reviewed literature by theme, organized into twenty clusters of ten sources each. Each cluster names the specific studies it draws on, states what those studies found or argued, and explains how the findings relate to the advertising budget allocation and measurement governance problem addressed in this review. Directly relevant sources inform the framework's focal constructs; sources drawn from other sectors are labeled analogical and are used only to illustrate a transferable mechanism, never as direct empirical evidence about financial services marketing. (Chen & Yucesan, 2005; Pletneva et al., 2018).

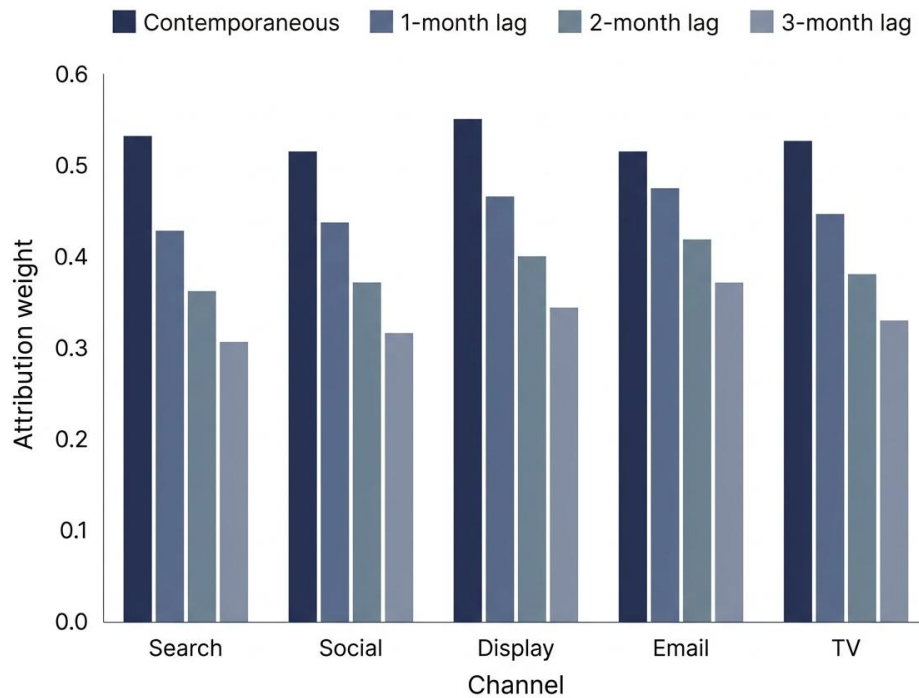


Figure 2. Attribution weight by channel and lag.

The first evidence group converges on a single theme: analytics only creates value once it is wired into a specific, accountable decision (Sakya et al., 2022). For financial services marketing, the transferable mechanism is governed ownership, not raw analytic sophistication. (Kumar & Sharma, 2017; Micco et al., 2011).

The second evidence group shifts from ownership to data governance as the binding constraint on analytic value. The transferable mechanism for financial services marketing is that data governance, not model sophistication, is usually the first-order constraint on incremental risk adjusted marketing return. (McNulty & Inkson, 2013; Micco et al., 2004).

The third evidence group turns to the interoperability problem: systems and metrics that work well in isolation often fail when linked. For financial services marketing, the implication is that channel, campaign, and customer data must share a common schema before cross-channel measurement, such as channel interaction and budget optimization, can be trusted. (Potluri & Muuka, 2021).

The fourth group addresses a different constraint: how quickly a model's benefit decays once conditions change. Incrementality estimates in advertising should therefore be treated as perishable and scheduled for recalibration, not adopted once and assumed to remain valid. (Madsen & Niessner, 2014).

The fifth evidence group is the most directly relevant to incrementality and budget discipline (Dada et al., 2021).

The sixth evidence group returns to marketing measurement directly, with two analogical sources included for methodological contrast.

The seventh group examines how forecasting and segmentation models translate into marketing decisions specifically. (Farjam & Hongyi, 2015).

The eighth evidence group is the most heterogeneous, deliberately combining direct and cross-sector sources. Taken together, the cluster supports treating data definition and unit consistency, not model sophistication, as the primary quality gate for financial services marketing analytics. (de Mesquita & Kostelijn, 2021; Zerres, 2018).

The ninth group centers on governance-optimization trade-offs.

The tenth group examines what happens when governance and optimization are evaluated together rather than sequentially.

The eleventh group focuses on accountability architecture.

The twelfth group closes the risk and control theme with evidence on delayed payoffs.

The thirteenth group turns to automation governance specifically.

The fourteenth group examines valuation and readiness under uncertainty.

The fifteenth group addresses early-warning and leading-indicator design.

The sixteenth group turns to decision bias and prioritization.

The seventeenth group returns to implementation fidelity, a condition named explicitly in propositions P1 through P6.

The eighteenth group examines training and capability building as a precondition for the gains documented elsewhere in this review. (Wang et al., 2017).

The nineteenth group closes on reporting and board-level accountability.

The twentieth and final evidence group closes the review by returning to accountability at the portfolio level. Read across all twenty clusters, the recurring mechanism is the same one this review places at the center of its framework: value is realized when a signal, however sophisticated, is routed through a governed, accountable, and consistently defined decision.

7 Implications and Conclusion

Six disciplines follow from the framework. Start with the decision, not the available dashboard: define who decides, what alternatives exist, which baseline represents no action, and how long outcomes should be observed. Keep one governed metric dictionary at the center of advertising budget allocation, with formulas, owners, source systems, exclusions, refresh cycles, and validation tolerances attached to every measure.

Distinguish prediction from causal contribution: a model that forecasts response or risk does not, by itself, show that an intervention creates value. Report distributional outcomes rather than averages, because mean performance can hide concentrated losses, customer harm, regional gaps, or burdens shifted to another function. Adopt staged approval: pilot, validate, expand, and review through predefined gates linked to evidence quality and risk appetite. Finally, keep a human accountable: automated recommendations need documented override rights, monitoring, and an appeal or remediation path whenever decisions affect customers or counterparties.

The research agenda is correspondingly concrete. Outcome-measure work should preregister a single primary measure, the observation window, the treatment definition, and the missing-data rule before data collection begins, and report any secondary measures explicitly as secondary. Later work should compare alternative valuation assumptions, study model drift, and test how governance quality affects realized benefits. Researchers should publish negative and null findings, report subgroup effects, and separate statistical significance from economic materiality, and replication packages should include data dictionaries, codebooks, model cards, and decision logs whenever confidentiality permits.

First, the recurring lesson of this review is that analytical sophistication pays off only when routed through a governed, accountable, and consistently defined decision; across settings as different as customer service analytics, venture capital fraud detection, and public sector audit reform, value is realized when a signal is wired into a specific, owned intervention. Second, the framework defines incremental risk adjusted marketing return as a multi period, risk adjusted outcome and links it to six operational dimensions, incrementality, media attribution, brand carryover, channel interaction, budget optimization, and measurement governance, whose interactions must be evaluated jointly rather than one metric at a time. Third, its main contribution is an auditable chain from data and assumptions to intervention, outcome, challenge, and learning; the review does not present employer specific findings or claim empirical validation, and it offers a structured foundation for future testing and for management decisions that require commercial performance, resilience, customer impact, and regulatory accountability to be assessed together.

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