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Are Display Ad Content and Landing Page Ad Content Complements or Substitutes? A Field Experiment

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Are Display Ad Content and Landing Page Ad Content Complements or Substitutes? A Field Experiment *

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Abstract

We study whether sequential ad content – display ads and landing page ads – act as substitutes or complements using a field experiment with a semiconductor firm. Ad headlines emphasizing product quality or transactional ease were randomly assigned across two ad placements in eight markets. Using pre-experiment organic traffic to infer prior knowledge about the advertised products, we find that the relationship between the two contents varies with prior information. In low-information markets, two quality-focused contents across placements showed substitutability, consistent with ad content serving as a source of information. In high-information markets, they exhibited complementarity, suggesting their preference-matching role. Decomposing quality-focused content reveals that content emphasizing horizontal match drives information provision, whereas content highlighting vertical quality supports preference matching. Our findings suggest that even coarse, market-level coordination of sequential ad content substantially improves online customer acquisition – lowering cost per action by 37%.

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1 Introduction

When a customer clicks on an online display ad, they are directed to a landing page which also features content selected by the advertiser, sometimes in the form of banner ads placed on the landing page. Should advertisers highlight similar content on the two ad placements, or should they feature different contents? Understanding the relationship between the two contents not only improves online customer acquisition through better ad content coordination but also offers insights into the underlying role of advertising in the customer journey. If the initial ad acts as a matching device that aligns the product with customer preferences (a preference-matching role), subsequent landing page content that reinforces the same message is expected to increase engagement, indicating complementarity. In contrast, if the first ad primarily serves as an informational source (an informative role), repeating similar content may be less effective than presenting different content, suggesting substitutability. If the first ad functions merely as a navigational shortcut to the website, its content should have no meaningful interaction with that of the landing page.

Despite the practical and theoretical relevance, the joint effect of display ad and landing page contents remains underexplored, perhaps due to challenges in data collection and identification. Establishing the causal impact of advertising content can be challenging without a field experiment (Gordon et al. 2019), and studying interactions between two advertising contents requires that both contents vary independently.

We examine the relationship between sequential contents through a large-scale field experiment with a semiconductor manufacturer. We hypothesize that the underlying role of ad content – as a a source of information, a preference-matching device, or a navigational shortcut – is inferred based on whether similar contents act as complements, substitutes, or independent goods when sequentially presented. As the literature on advertising exposure underscores the importance of prior knowledge in advertising effectiveness (Ackerberg 2001, Ackerberg 2003, Sethuraman et al. 2011, Honka et al. 2017, Ursu et al. 2022), we assess whether the effects of two sequential contents change based on customers' prior information, proxied by pre-experimental searches for the company and product names. This measure of prior information – which we refer to as *named searches* – builds on the literature employing branded search (Rutz and Bucklin 2011, Blake et al. 2015, Narayanan and Kalyanam 2015, Honka et al. 2024) and is strongly correlated with other information proxies we find in the pre-experimental browsing data.

Our field experiment took place in eight markets (four products × two regions) over four months. Jointly with the semiconductor company, in each market, we developed and tested four ad headlines highlighting one of the two types of product quality – vertical quality or the likelihood of finding a horizontal match – alongside the business-as-usual headline about transactional ease as the baseline. This results in a total of 40 ad headline-market combinations (5 headlines per market × 8 markets) in our experimental design.[1] These content types – product quality (vertical, horizontal) and transactional ease – address key drivers of search and purchases in online purchasing contexts and align with variations in ads along the marketing purchase funnel.[2] We randomly assigned these headlines in display ads and subsequent landing page ads on the company's website across markets.[3]

As the outcome variables, we analyze 1) display ad click-through rates at the day-market level collected by an ad network and 2) "action rates" or web-mediated direct response rates (e.g., sample orders, inquiries to the sales team, and downloads of product specification sheets) at the IP level conditional on the display ad click. In a B2B context, where conversion cycles are significantly longer than in B2C settings (TrustRadius 2024, Thomas et al. 2023), web-mediated direct responses serve as a valuable proxy for customer relationship management and future conversion potential. Consistent with standard

[1]Examples of product quality ads include "*FIT [Failures in time] rate less than 0.5*" (vertical quality) and "*Used in over XX applications*" (match likelihood). For match likelihood ads, rather than targeting specific horizontal preferences, we highlight the broad variation of the company's offering or its ability to meet diverse customer needs to increase the perceived likelihood of finding a match for all customers regardless of their horizontal preferences. Examples of transactional ease content include "*Inventory available*" which implies faster delivery and "*Contact us*" which is commonly used as a call-to-action message promoting easy access to the service.

[2]Product information is typically highlighted in the upper funnel to build awareness, while call-to-action messaging is commonly employed in the lower funnel to drive conversions.

[3]The experiment costed $312,000 given the scale and double layers of randomization.

practice, display ad click-through data were collected by the ad network as aggregated impressions and realized clicks at the day–market level rather than at the individual IP-level. However, downstream engagement data were available at the IP level, indicating which display ad content was clicked before arriving at the website.

The experimental results first establish that both display ad and landing page ad content individually serve as a source of information, whose effects on customer engagement vary substantially by prior information available in the market. In markets with less prior knowledge of the advertised products (i.e., with lower named searches in the pre-experiment period), ads highlighting product quality generate higher click-through rates and action rates than ads featuring transactional ease. However, the same headlines significantly *underperform* in high-information markets. Ignoring this market-level heterogeneity leads to an inaccurate conclusion of the null effect of ad content. Also, display ad content exhibits carryover effects on downstream action rates: headlines that generate higher click-through rates – quality-focused content in low-information markets and transaction-focused content in high-information markets – also lead to higher downstream action rates, contrary to the common marketing trade-offs between traffic and conversion. These patterns suggest that display ads serve more than a navigational shortcut to the advertiser's website, delivering information that online customers actively process.

The joint effect of the two sequential ad contents varies with prior information. In low-information markets, the interaction effect between two quality-focused contents is negative, indicating substitutability. Specifically, landing page ad on product quality has a weaker effect on customer actions when it follows similar display ad content on product quality than when it follows different display ad content on transactional ease. In contrast, in high-information markets, the interaction effect becomes positive, indicating complementarity. The findings suggest that the role of product-quality ads – relative to transactional-ease ads – varies with prior knowledge: it primarily serves as an information source in low-information markets, while in high-information markets it attracts customers with specific preferences. Decomposing ad content on product quality into two subtypes reveals that ad content emphasizing match likelihood primarily drives information provision in low-information markets, while content featuring vertical quality drives preference matching in high-information markets. These diverging patterns across ad content types indicate that relying solely on ad exposure to measure advertising effects can offer limited insights.

Prediction exercises with causal estimates of ad content effects highlight the economic value of sequential ad content coordination at the market level. Compared to the business-as-usual scenario (where both display and landing page contents were all transaction-focused), the best scenario (assigning action-maximizing sequence of display ad and landing page ad contents) achieves a 3.9% increase in total clicks, a 69.2% increase in customer actions, and a 37.2% decrease in cost per action on averge, given the fixed display ad impressions.[4] Importantly, targeting display ad content or landing page ad content alone yields much smaller increase in actions, suggesting that coordinating the two contents can significantly improve online customer acquisition.

Our findings provide an easily implementable framework for marketers to enhance online customer acquisition through ad content design. First, our results show that the effect of ad content on customer action depends on customers' prior information and the types of ad content presented *in sequence*. Beyond simply serving quality-focused (or transaction-focused) content in low- or high-information markets, firms can further increase customer actions by strategically sequencing the two contents, leveraging complementarities that vary across content types. Second, we show that market-level search data can be strong proxies for prior customer knowledge and guide how to coordinate display ad and landing page content. Not relying on individual data, this approach ensures privacy compliance and mitigates the cold-start problem for new customers with no prior interactions (Padilla and Ascarza 2021).

We demonstrate that advertising content plays a critical role in B2B environments. Digital advertising is often viewed as less relevant in B2B contexts as customers are pre-

[4]Since the experiment took place in 2023 when the microchip shortage was still perceived to be influencing market dynamics, we interpret the effect of the business-as-usual scenario highlighting transactional ease as likely elevated relative to normal conditions. Therefore, any positive effect of vertical-quality and match-likelihood content can be viewed as conservative.

sumed to be information-savvy and more rational. However, the nearly $21 billion spent on B2B online advertising in the U.S. in 2025 suggests otherwise (eMarketer 2024). This paper helps resolve this puzzle by offering experimental evidence on the informational role and preference-matching role of advertising in a B2B setting, providing actionable insights for firms.

Relevant Literature This study contributes to the theoretical and empirical literature on online advertising content. Prior research has shown that advertising influences consumer behavior through informative and persuasive channels, using data on *ad exposure* (Nelson 1974, Milgrom and Roberts 1986, Ackerberg 2001, Erdem and Keane 1996, Sahni and Nair 2019) in specific decision-making stages (Honka et al. 2017, Seiler and Yao 2017). An emerging stream of literature investigates how different ad contents influence consumer behavior (Liaukonyte et al. 2015, Sudhir et al. 2016, Bruce et al. 2017, Tsai and Honka 2021, Guitart and Stremersch 2021, Morozov and Tuchman 2024, Banerjee and Urminsky 2024). However, few studies focus on the relationship between two sequential advertising contents. By testing the joint effects of two consecutive advertising contents by the same advertiser, we show the economic significance of ad content coordination and demonstrate the dual role of advertising content depending on the prior information. Our work complements recent studies such as Morozov and Tuchman (2024) which uses lab data to assess the effects of price and genre ads in an online bookstore setting, and Banerjee and Urminsky (2024) which examines how the presentation of information (e.g., positive or negative tone, first-person or second-person) shapes consumer response. It also complements Rafieian and Yoganarasimhan (2022) and Rafieian (2023), which examine how the sequencing of advertising content across different brands influences customer behavior at the platform level, as well as Sahni et al. (2019), which documents intertemporal complementarities in advertising exposure through a retargeting experiment.

This paper adds to the literature on customer relationship management, more specifically on the "cold start problem" (Padilla and Ascarza 2021). Our findings complement probabilistic content engineering methods for inferring customer heterogeneity in the absence of individual-level histories (Hauser et al. 2009, Lee et al. 2018) by 1) leveraging market-level data to capture variation in customers' prior information, 2) demonstrating that prior information helps predict heterogeneity in ad content effectiveness across markets, and 3) offering insights into how to coordinate ad content across multiple online real estates.

2 The Effects of Two Consecutive Advertising Contents: Conceptual Framework

We formalize predictions about how a sequence of consecutive ad contents influences customer decisions under three distinct assumptions about its role: as a source of information, a preference-matching device, or a navigational shortcut. Each assumption yields different predictions, which we test empirically using the experimental data.

2.1 Utility

Customer i has the following utility from purchasing product j:

$$u_{ijt} = u(q_{ijt}, d_{ijt}) = \underbrace{q_{ijt}}_{=v_{ijt}+h_{ijt}} + d_{ijt}. \tag{1}$$

Customer i's choice utility has two main components: (i) perceived product quality (q_{ijt}), which can be further decomposed into vertical quality (v_{ijt}) and horizontal match value (h_{ijt}); and (ii) perceived transactional ease (d_{ijt}). Examples of transactional ease include fast delivery (e.g., ready-to-ship inventory), convenient payment options (e.g., Apple Pay that removes the need to enter address and card details), accessible customer service (e.g., guaranteed response within 24 hours), and short lead times in B2B markets. Both product quality and transactional ease are widely recognized as central drivers of online demand beyond our specific setting (Fisher et al., 2019; Gui & Drerup, 2022;

Tounekti et al., 2019).

There exist three time periods in our model. Period 0 represents the period before customer i is exposed to an online ad. Period 1 occurs when customer i is exposed to an online display ad and decides whether to click on it. Period 2 represents the stage where customer i, conditional on clicking the ad in Period 1 and arriving at the company's landing page, decides whether to engage further after being exposed to a landing page ad.

Let $\mathcal{A} = \mathcal{Q} \cup \mathcal{D}$ denote the set of possible ad content, where ads focus either on product quality ($\mathcal{Q}$) or on transactional ease ($\mathcal{D}$). A display ad $A_1 \in \mathcal{A}$ and a landing page ad $A_2 \in \mathcal{A}$ each convey content relevant to one of the two utility components $\theta \in \{q, d\}$ as their primary content. Although ads may highlight multiple elements, headlines typically emphasize a single dimension, especially in online contexts where customer attention is limited. This assumption is consistent with prior research on ad content effects (Biswas 2020, Morozov and Tuchman 2024). The set of quality-focused content ($\mathcal{Q}$) consists of content emphasizing vertical quality ($\mathcal{V}$) and content promoting the likelihood of a good match ($\mathcal{H}$): $\mathcal{Q} = \mathcal{V} \cup \mathcal{H}$. As evaluating the effects of ad content requires a baseline for comparison, we set the transactional-ease ad $\mathcal{D}$ as the baseline and assess the relative effectiveness of other content types against this benchmark.

In each period, customer i decides whether to engage after viewing the ad according to the following decision rule:

Period 1 (after viewing display ad A_1):

$$U_{ij1}(A) = \underbrace{q_{ij1}(A_1) + d_{ij1}(A_1)}_{\substack{\text{Ad updating beliefs} \\ \text{(“Informative advertising”)}}} + \underbrace{\rho_{iq}\mathbb{1}\{A_1 \in \mathcal{Q}\} + \rho_{id}\mathbb{1}\{A_1 \in \mathcal{D}\}}_{\substack{\text{Ad increasing utility when content matches preferences} \\ \text{(“Preference-matching advertising”)}}} \tag{2}$$

Click a display ad iff $U_{ij1} > 0$

Period 2 (after viewing a landing page ad A_2, conditional on $U_{ij1} > 0$)

$$U_{ij2}(A_2|A_1) = \underbrace{q_{ij2}(A_2|A_1) + d_{ij2}(A_2|A_1)}_{\substack{\text{Ad updating beliefs} \\ \text{(“Informative advertising”)}}} + \underbrace{\rho_{iq}\mathbb{1}\{A_2 \in \mathcal{Q}\} + \rho_{id}\mathbb{1}\{A_2 \in \mathcal{D}\}}_{\substack{\text{Ad increasing utility when content matches preferences} \\ \text{(“Preference-matching advertising”)}}} \tag{3}$$

Take action iff $U_{ij2} > 0$.

Equations 2 and 3 capture two channels through which advertising content affects consumer utility (see Bagwell 2007 for a review). The first channel – the informative role of advertising – updates consumers' beliefs about product quality or transactional ease by providing information that is otherwise costly to acquire. Accordingly, consumer beliefs q_{ijt} and d_{ijt} are modeled as functions of ad content A_1 and A_2. The second channel – the preference-matching role of advertising – directly shifts utility through consumer-specific preference for each content type (ρ_{iq} and ρ_{id}).[5] Importantly, we assume that the preference-matching channel temporarily boosts customer utility and encourages continuation to the next period without any carryover effect once the new period begins, whereas the learning channel has a persistent effect through updated beliefs.[6]

2.2 Ad content as a source of information

Assumption 1. In Period t, customers have imperfect information about q and d characterized as a Normal distribution:

$$\boldsymbol{\theta}_{ijt} \sim N(\overline{\boldsymbol{\theta}}_{ijt}, \boldsymbol{\Sigma}_{ijt}) \quad \text{where } \overline{\boldsymbol{\theta}}_{ijt} = \begin{bmatrix} \underbrace{\overline{q}_{ijt}}_{=\overline{v}_{ijt}+\overline{h}_{ijt}} \\ \overline{d}_{ijt} \end{bmatrix} \text{ and } \boldsymbol{\Sigma}_{ijt} = \begin{bmatrix} \underbrace{1/\lambda_{ijqt}}_{=1/\lambda_{ijvt}+1/\lambda_{ijht}} & 0 \\ 0 & 1/\lambda_{ijdt} \end{bmatrix} \tag{4}$$

Assumption 1 allows customers to hold different amount of information for the two utility components of product j. Lower precision (λ) means less prior information or certainty about the element. This characterization aligns with a latent intent framework (Broder 2002, Wang et al. 2024) or a conversion funnel perspective (Hoban and Bucklin

[5]This is similar to how persuasive advertising is characterized in the literature (Nelson 1974, Ackerberg 2001).

[6]Under this definition, any ad content that induces lasting changes in customer preferences is considered informative. For example, a brand ad that leads to enduring shifts in customers' perceptions (e.g., Dove's *Real Beauty* campaigns) is viewed as informative that leads to customer learning. In contrast, if a brand ad triggers only temporary behavioral changes (e.g., an ad with an image of an icy-cold glass of Coke prompting a one-time purchase), it is characterized as preference-matching.

2015, Honka et al. 2017); low precision in customers' prior beliefs about product quality corresponds to high search intent or being in the awareness stage, while high precision corresponds to high purchase intent or being in the conversion stage.

Assumption 2. An ad $A_t \in \mathcal{A}$ delivers an information signal $\tau_\theta \sim N(\overline{\tau}_\theta, 1/\lambda_\tau)$ for $\theta \in \{q, d\}$ which has the following properties: 1) it weakly increases customer i's respective prior mean (i.e., $\overline{\theta}_{ijt} < \overline{\tau}_\theta$) and 2) it has the same precision of 1 as a signal ($\lambda_\tau = 1$) regardless of its content (q or d).

The first part of Assumption 2 states that advertising does not reduce demand.[7] The second part assumes that the content of the ad does not affect the precision of the ad signal distribution – that is, an ad is not perceived as significantly more or less noisy depending on its content. This is an implicit assumption in consumer learning models that assess the effects of advertising exposure, where the precision of ad signals is held constant within a given ad medium (Erdem and Keane 1996). This allows any differences in the ratio of prior to signal variance across customers to be attributed to differences in their prior variance.

In Period t, after viewing an ad for product j highlighting feature θ, customer i's belief about feature θ of product j is updated as follows:

$$\theta_{ijt} = (1 - \omega^\theta_{ijt}) \cdot \theta_{ijt-1} + \omega^\theta_{ijt} \cdot \tau_\theta \quad \text{where} \quad \omega^\theta_{ijt} = \frac{\lambda_\tau}{\lambda_{ij\theta t-1} + \lambda_\tau} \quad \forall \theta \in \{q, d\} \tag{5}$$

$$\lambda_{ij\theta t} = \lambda_{ij\theta t-1} + \lambda_\tau \tag{6}$$

Equations (5) and (6) have three implications. First, the effect of ad content on customer utility in each period is a function of the amount of prior information (i.e., the precision of the prior distribution): the lower the precision of prior beliefs about product quality, the greater the weight placed on quality-focused ad content in belief updating. Second, the effect of ad content in Period 1 (display ad) carries over to Period

[7] We assume that ad content related to horizontal match value ($A_t \in \mathcal{H}$) emphasizes the broad appeal or the variance of the company's offering – highlighting their ability to meet diverse horizontal needs rather than catering to a single type of horizontal preference – such that the expected likelihood of finding a match weakly increases for all customers regardless of their specific preferences.

2 (landing page), as customer i's beliefs in Period 2 are shaped by the ad content they were exposed to in Period 1. The belief updating rule suggests that this carryover effect is also a function of the precision of prior beliefs about quality. Third, all else equal, the effect of landing page ad content is greater when it differs from the preceding display ad content than when it is similar; i.e., the two contents are substitutes for a given customer. For example, the precision of a customer's prior belief on product quality will increase (i.e., λ_{ijqt} will increase) when she reaches the landing page through a display ad highlighting product quality. Therefore, a landing page ad featuring product quality will induce a smaller incremental update when the preceding display ad already featured product quality than when it featured transactional ease. These lead to our first set of formal hypotheses.

Proposition 1. (Informative Ad Contents) Suppose the informative effect of ad content dominates, i.e., ad content mainly serves as a source of information. Then, 1) the effect of ad content on product quality on customer decisions within each period decreases with customers' prior information amount (H1-1), 2) ad content on product quality in Period 1 (display ad) has a carryover effect on action rates in Period 2 which decreases with customers' prior information amount (H1-2), and 3) two quality-focused ad contents presented consecutively act as substitutes; that is, the marginal effect of the second ad content on quality is smaller when it follows the display ad content on quality than when it follows the display ad content on transactional ease (H1-3). Formal proofs are provided in Section A.

$$\frac{\partial(E[U_{ijt}(A_t \in \mathcal{Q}) - U_{ijt}(A_t \in \mathcal{D})])}{\partial \lambda_{iq0}} < 0 \quad \text{for } t \in \{1, 2\} \tag{H1-1}$$

$$\frac{\partial(E[U_{ij2}(A_1 \in \mathcal{Q}) - U_{ij2}(A_1 \in \mathcal{Q})])}{\partial \lambda_{iq0}} < 0 \tag{H1-2}$$

$$E[U_{ij2}(A_2 \in \mathcal{Q}|A_1 \in \mathcal{Q}) - U_{ij2}(A_2 \in \mathcal{D}|A_1 \in \mathcal{Q})|U_{ij1}(A_1 \in \mathcal{Q}) > 0]$$

$$< E[U_{ij2}(A_2 \in \mathcal{Q}|A_1 \in \mathcal{D}) - U_{ij2}(A_2 \in \mathcal{D}|A_1 \in \mathcal{D})|U_{ij1}(A_1 \in \mathcal{D}) > 0] \tag{H1-3}$$

2.3 Ad content as a preference matching device

Ad content may also function as a preference-matching device, attracting customer pools whose preferences align with the specific message. For instance, ads emphasizing quality are more likely to draw quality-sensitive customers, while ads highlighting fast shipping (as an aspect of transactional ease) appeal to time-impatient customers. This preference-matching role of advertising can be effective even when consumers already have full information about the product. In the model, this corresponds to $q_{ijt}(A_t) = q_{ij}$ and $d_{ijt}(A_t) = d_{ij}$: consumers' beliefs about quality and transactional ease remain unchanged regardless of the ad content, but their utility increases when ad content matches their preferences.

We assume that the preference-matching effects are not systematically correlated with each other. As a result, exposure to one ad content affects only the distribution of its own preference-matching parameter in the next period without influencing the distribution of the other.

Assumption 3. The effectiveness of quality-focused ad content as a preference-matching device, ρ_{iq}, and that of transaction-focused ad content, ρ_{id}, are independently distributed.

$$\rho_{iq} \perp\!\!\!\perp \rho_{id}. \tag{7}$$

This mechanism differs from the learning model in three ways. First, while the preference-matching model predicts heterogeneity in ad content effects, it does not predict specific patterns of the heterogeneity as a function of prior information amount within a market. Since the distribution of preferences for messaging about quality and transactional ease can take any shape, the model remains agnostic about which content will perform better in a given market unless additional data exist about such preferences. Second, the preference-matching mechanism predicts no carryover effect of display ad content on subsequent action rates at the landing page, whereas the learning model does. Third, unlike the learning model, the matching model predicts that landing page ad content that contains similar information with the preceding display ad content generates more engagement, implying realized complementarity between the two contents.[8] For example, the matching model predicts that transaction-focused landing page ads are more effective when they follow transaction-focused display ads than when they follow quality-focused display ads, as customers are likely to have higher preferences for messaging that they clicked through. This prediction contrasts with that of the learning model, which suggests that the preceding display ad content undermines the effect of the following landing page ad content if the two are similar.

Proposition 2. (Preference-matching Ad Contents) Suppose the preference-matching effect of advertising content dominates, i.e., ad content mainly serves as a preference matching device. Then, 1) the effect of ad content in each period is not correlated with customers' prior information amount (H2-1), 2) ad content on product quality in Period 1 (display ad) does not have a carryover effect on action rates in Period 2 (H2-2) and 3) similar ad contents presented consecutively act as complements; i.e., the marginal effect of the second ad content is larger when it repeats the preceding ad content than when it introduces different content (H2-3). Formal proofs are provided in Section A.

$$\frac{\partial(E[U_{ijt}(A_t \in \mathcal{Q}) - U_{ijt}(A_t \in \mathcal{D})])}{\partial \lambda_{iq0}} = 0 \quad \text{for } t \in \{1, 2\} \tag{H2-1}$$

$$E[U_{ij2}(A_1 \in \mathcal{Q}) - U_{ij2}(A_1 \in \mathcal{D})]) = 0 \tag{H2-2}$$

$$\begin{aligned} &E[U_{ij2}(A_2 \in \mathcal{Q}|A_1 \in \mathcal{Q}) - U_{ij2}(A_2 \in \mathcal{D}|A_1 \in \mathcal{Q})|U_{ij1}(A_1 \in \mathcal{Q}) > 0] \\ &> E[U_{ij2}(A_2 \in \mathcal{Q}|A_1 \in \mathcal{D}) - U_{ij2}(A_2 \in \mathcal{D}|A_1 \in \mathcal{D})|U_{ij1}(A_1 \in \mathcal{D}) > 0] \end{aligned} \tag{H2-3}$$

2.4 Ad content as a navigational shortcut

In the simplest case, ad content works only as a navigational device that provides a mental and physical shortcut to the company's product page. If this is the leading mechanism, there should be no differences in the outcomes under different ad contents,

[8] We use the term "realized complementarity" to emphasize that, in the model, complementarity arises not within a given customer but across customers selected under different display ads.

as long as the company and product names are visible in the same way. In the model, this implies that consumer utility remains the same regardless of the ad content.

Proposition 3. (Navigational Ad Contents) If ad content serves as a navigational shortcut, then 1) three ad content types yield the same effect sizes (H3-1), 2) ad content in Period 1 does not have any carryover effect in Period 2 (H3-2), and 3) the effects of two consecutive ad contents are independent – i.e., the marginal effect of the second ad content is the same regardless of the preceding ad content (H3-3).

$$E[U_{ijt}(A_t \in \mathcal{Q}) - U_{ijt}(A_t \in \mathcal{D})] = 0 \quad \text{for } t \in \{1, 2\} \tag{H3-1}$$

$$E[U_{ij2}(A_1 \in \mathcal{Q}) - U_{ij2}(A_1 \in \mathcal{D})] = 0 \tag{H3-2}$$

$$\begin{aligned} &E[U_{ij2}(A_2 \in \mathcal{Q}|A_1 \in \mathcal{Q}) - U_{ij2}(A_2 \in \mathcal{D}|A_1 \in \mathcal{Q})|U_{ij1}(A_1 \in \mathcal{Q}) > 0] \\ &= E[U_{ij2}(A_2 \in \mathcal{Q}|A_1 \in \mathcal{D}) - U_{ij2}(A_2 \in \mathcal{D}|A_1 \in \mathcal{D})|U_{ij1}(A_1 \in \mathcal{D}) > 0] \end{aligned} \tag{H3-3}$$

Table 1 summarizes the hypotheses under the three different roles of ad content.

Table 1: Summary of hypotheses

The role of ad content	Predictions about the effect of quality-focused content relative to transaction-focused content		
	Main effect within each period	Carryover effect on downstream action	Relationship between two contents
Informative	Decreases with prior information amount (H1-1)	Decreases with prior information amount (H1-2)	Substitutes (H1-3)
Preference-matching	Does not change with prior information amount (H2-1)	Zero carryover effect (H2-2)	Complements (H2-3)
Navigational	Zero main effect (H3-1)	Zero carryover effect (H3-2)	Independent (H3-3)

3 Field Experiment

3.1 Empirical context

We collaborated with a semiconductor manufacturing company that produces microchips with a relatively new technology. The setting highlights the importance of understanding the effects of ad content for several reasons. First, the semiconductor market is information-intensive and heavily relies on online advertising to distribute product information. Customers (corporate engineers) start their journey – which is over 6 months on average according to our collaborator's client survey – with finding brief information about products (microchips) from information aggregator websites (where display ads are shown) and explore individual manufacturers' websites for detailed information. It is critical for companies to provide their potential customers relevant information at these digital touchpoints. Second, as the manufacturer serves a wide range of customer needs through their broad product lines, it becomes a complicated decision to select relevant information for different products and customers. Various product features, usage scenarios, and lead times can all influence demand, making them potential candidates for ad content. Third, in the case of our collaborator, despite the low likelihood of impulse clicks given the nature of the products, nearly 80% of the traffic through display ads leave the company's website immediately ("bounce") after viewing the landing page. This high bounce rate indicates the need for investigating whether providing different content on the landing page can effectively improve post-ad-click customer engagement. Finally, not all customers are fully informed about the company or its products, as only 18% of their potential customers (engineers) across the countries are aware of the core technology the company uses based on a proprietary survey. This gives sufficient variations across markets in prior information about the company and its products, allowing us to test both the informative and preference-matching roles of advertising.

Like in many B2B companies with long purchase cycles, direct conversion from an advertising campaign is hard to measure in our empirical context. Most microchip purchases are made outside the company's website through a major distributor, which makes it even harder to link conversion to specific advertising efforts. As online engagement (e.g., downloading data sheets of product specifications, creating an account) observed within the company's website is considered a proxy for conversion, we focus on within-website engagement measures ("action rates") and display ad click-through rate as our outcome variables of interest.

3.2 Field experiment design

3.2.1 Overview

From February 2, 2023 to June 13, 2023, we ran a field experiment where both display ad headlines and landing page ad headlines were randomized. The first layer of randomization occurred on an ad network, where display ad headlines were randomly varied between product quality (which is further decomposed into vertical quality and match likelihood) and transactional-ease content. Once a customer clicked on the display ad, the system endowed her with a unique ID and recorded which ad content she viewed. When the customer arrived at the landing page for the advertised product, the second layer of randomization took place, where one headline was randomly shown in a floating box on the side of the landing page. We tracked individual webpages that the customer browsed within the company's website to record whether they took action or not.

Figure 1 and 2 show examples of ad content manipulations. The ad network requires a standardized visual format for any display ad, which mutes variations in non-textual visual cues (Figure 1). A landing page ad in a floating box was shown at a fixed location (Figure 2).

We conducted the experiment across eight distinct markets (defined as product-region pairs), which were expected to vary in prior knowledge about the quality of advertised products. These markets included four products (D, E, G, and S) and two geographic regions (North America and Western Europe), which differ in operating history and the degree of differentiation in customer needs. The two geographic regions span 43 countries,

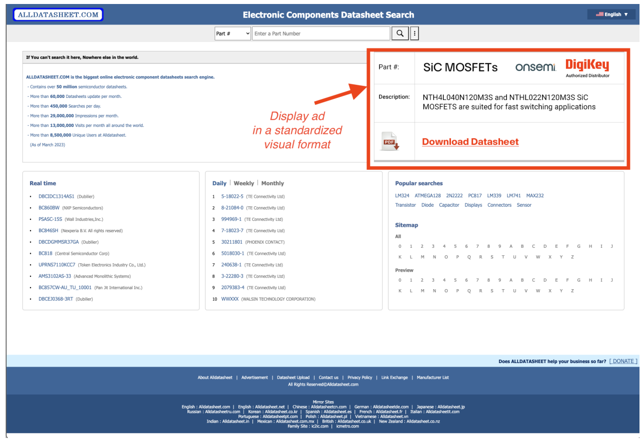


Figure 1: Standardized display ad: Example from a non-collaborating manufacturer

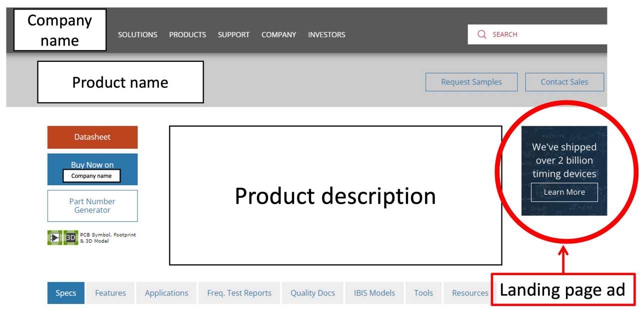


Figure 2: Experimental manipulation: Landing page ad

7 of which recorded more than 50 visits during the experiment.

3.2.2 Tested ad headlines

Our experiment tests a total of 40 headline–market combinations. Table 2 presents the product-specific headlines developed by the manufacturer's marketing and engineering teams. For the display ads, "Inventory Available" served as the business-as-usual transactional-ease headline, while the standard "Contact Support" was used as transaction-focused content for landing page ads. Product-quality headlines were tailored for each of the four products based on their characteristics, highlighting either vertical quality or match likelihood. The same set of headlines was used for both display ads and landing page ads, with the exception of the transaction-focused headlines.

While the classification of some headlines into content types may be open to interpretation, this reflects the practical realities of ad content creation. Although product

Table 2: Ad headlines tested in the field experiment

Product	Content type	Content (Headlines)	Content code
Product D & Product S	Transaction	*Inventory available* (Display ad; Product #S) *[Product name only]* (Display ad; Product #D) *Contact Support* (Landing page)	D
	Quality: Match likelihood	*Used in Over [N1] Applications*	H1
		Any [Spec], Always Available	H2
	Quality: Vertical	*Used By Over [N2] Customers*	V1
		>[Spec 1], <0.5 [Spec 2]	V2
Product E	Transaction	*Inventory available* (Display ad) *Contact Support* (Landing page)	D
	Quality: Match likelihood	*The Precision Timing Company*	H1
		Any [Spec], Always Available	H2
	Quality: Vertical	*We Have Shipped Over [N3] Devices*	V1
		>[Spec 1], <0.5 [Spec 2]	V2
Product G	Transaction	*Inventory available* (Display ad) *Contact Support* (Landing page)	D
	Quality: Match likelihood	*World's Broadest Line of Timing Solutions*	H1
		Any [Spec], Always Available	H2
	Quality: Vertical	*#1 Supplier of [product category name]*	V1
		>[Spec 1], < 1 [Spec 2]	V2

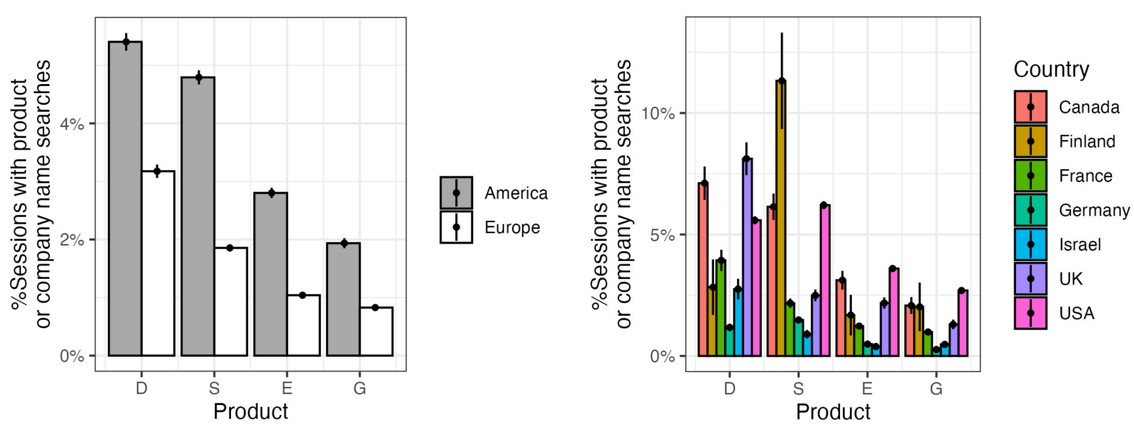
*Ad headlines have been redacted due to a non-disclosure agreement (marked with square brackets).

quality and transactional ease are distinct dimensions that advertisers can selectively emphasize, actual ad copies often convey both elements to varying degrees. By using company-created ad headlines within this conceptual framework, we test realistic ad content tailored to our empirical context and assess whether the differences in ad headlines influence customer decisions as predicted.

3.3 Inferring Prior Information from Pre-Experiment Data

To assess the role of prior information in ad content effects, we construct a market-level proxy for average customers' prior information about the quality of advertised products using pre-experiment organic traffic data. As customer-level or IP-level information is rarely available due to privacy constraints and a lack of prior interactions (the so-called "cold start problem," Padilla and Ascarza 2021), this market-level proxy provides a practical and flexible approach to inferring heterogeneity in customers' prior information even among first-time visitors.

For each market (product-region), we calculate the share of organic (non-ad-initiated) browsing sessions of the company's website that contain direct searches for product and company names from 2020 to 2022 prior to the experiment. We refer to this measure as *named searches*. Named searches are identified either through search engine queries that lead to browsing sessions on the company's website or through the use of the website's internal search feature to navigate to specific products. The share of named searches varies substantially across products and regions, revealing underlying heterogeneity (Figure 3(a)). The same measure constructed at a more granular product-country level also exhibits rich variation (Figure 3(b)).



(a) At the market (product-region) level

(b) At the product-country level

Figure 3: Named searches as a proxy of prior information (I)

We interpret named searches as being positively correlated with the amount of prior information about the advertised product's quality, or equivalently, with the *precision* of the prior quality (λ_{ijq0} in Equation (4)). For online customers to actively search for company or product names, they must already possess some knowledge about those. To validate this interpretation, we compare it with several additional indicators that are likely to correlate with customers' prior knowledge and show that the measure is significantly and positively correlated with 1) the likelihood of actions occurring within an organic session and 2) the share of returning IP addresses in pre-experiment organic traffic (see Appendix B.1).[9] We propose that this measure – similar to branded search employed by both academics and practitioners (Rutz and Bucklin 2011, Blake et al. 2015, Narayanan and Kalyanam 2015, Dotson et al. 2017) – is broadly applicable in settings where prior information serves as an important moderator.

We use the market(product–region)-level proxy of prior information in our main analysis because the display ad click data are available only at this level. As a robustness check, we employ a product–country level proxy when feasible, specifically in the landing page ad analysis. For the ease of interpretation in our later analysis, we normalize our market-level proxy (with 2 regions $\times$ 4 products = 8 data points) and product-country level proxy (with 7 countries $\times$ 4 products = 28 data points) to have a mean of 0 and a standard deviation of 1.

3.4 Experimental Data

For each ad headline, we obtained display ad click-through rates at the market-day level and detailed browsing data at the IP level conditional on ad clicks.[10]

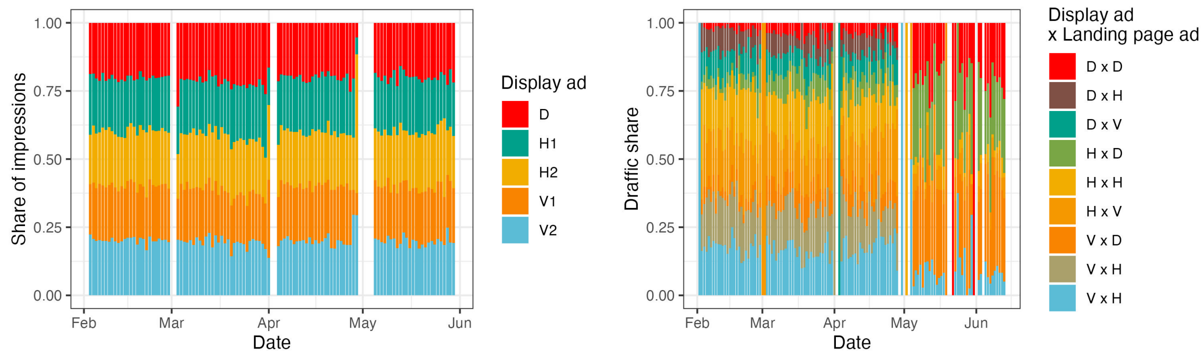
Figure 4 visually checks the randomization of ad headlines. Unlike display ad headlines, the randomization of landing page ad headlines was contaminated starting in May (Figure 4(b)).[11] As a result, we utilize display ad click-through data from the entire experimental period (from February to June), but limit the use of landing page and browsing data to the period up until April.

For the browsing data conditional on arriving at the landing page, we use within-

[9] The likelihood of customer actions is expected to be higher when customers already have sufficient prior information about the product of interest. A higher share of returning IPs suggests that online traffic consists of more repeat visitors, indicating greater prior information on average.

[10] The market-day level of CTR reporting aligns with standard ad platform practices; these platforms do not report individual-level data or provide information on users who did not click the ad.

[11] This was because the randomization feature was accidentally turned off by the company, which we caught after the experiment was over.



(a) Display ad

(b) Landing page ad

Figure 4: Randomization check

session action rates as our main outcome variables.[12] Specifically, for each IP address, we include only the first browsing session in the main analysis and measure within-session behaviors immediately following the initial exposure to the display ad to ensure clean identification.[13]

The final datasets used in our analyses comprise (1) 3,495 market-headline-day observations of impressions and clicks and (2) 13,576 market-IP-headline observations of action decisions conditional on arriving at the landing page. Table 3 reports average click-through and action rates by market and content type. Both metrics are higher under quality-focused content in markets with lower prior information and lower in markets with higher prior information.

4 Empirical Strategy

To examine whether the effect of quality-focused display ad content relative to transactional-ease content varies systematically with prior information about quality (Hypotheses H1-1, H2-1, and H3-1), we estimate the following regression:

$$CTR_{amt} = \beta_0 + \beta_1 Q_{amt}^{Display} + \beta_2 \widehat{I}_m + \beta_3 Q_{amt}^{Display} \times \widehat{I}_m + \epsilon_{amt}, \tag{8}$$

[12] A session is defined as ending when no browsing activity is recorded within the subsequent 30 minutes.

[13] During the experiment, 87% of IP addresses visited the website only once. As a robustness check, we re-estimate our regressions using action rates aggregated across all sessions within the experimental period and find similar results.

Table 3: Summary statistics by market and content type

(a) Click-through rates

Display ad content	Named search	Impressions (daily)				CTR (daily)			
		Transaction-focused		Quality-focused		Transaction-focused		Quality-focused	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Market 1	0.008	412.14	274.67	422.64	291.86	0.025	0.013	0.026	0.013
Market 2	0.010	419.57	251.01	421.66	250.60	0.024	0.012	0.029	0.016
Market 3	0.019	380.06	287.49	416.70	309.86	0.023	0.017	0.027	0.028
Market 4	0.019	462.72	244.69	459.83	259.67	0.024	0.012	0.025	0.011
Market 5	0.028	473.67	346.29	476.89	334.38	0.022	0.011	0.024	0.011
Market 6	0.032	419.43	431.13	424.24	372.70	0.029	0.032	0.029	0.062
Market 7	0.048	431.02	286.80	444.46	265.00	0.030	0.032	0.023	0.026
Market 8	0.054	463.41	275.10	460.36	255.91	0.031	0.047	0.026	0.021

**Markets (product-region pairs) are numbered in ascending order of the prior information proxy.*

(b) Action rates

Landing page ad content	Action rate (within session)				Action rate (across sessions)			
	Transaction-focused		Quality-focused		Transaction-focused		Quality-focused	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Market 1	0.010	0.102	0.025	0.155	0.017	0.131	0.027	0.162
Market 2	0.005	0.067	0.012	0.110	0.005	0.067	0.016	0.127
Market 3	0.000	0.000	0.007	0.081	0.000	0.000	0.009	0.092
Market 4	0.020	0.140	0.022	0.146	0.034	0.182	0.029	0.169
Market 5	0.015	0.121	0.021	0.143	0.015	0.121	0.027	0.161
Market 6	0.027	0.164	0.022	0.145	0.027	0.164	0.022	0.145
Market 7	0.006	0.080	0.008	0.089	0.016	0.126	0.014	0.115
Market 8	0.016	0.127	0.014	0.116	0.025	0.155	0.018	0.134

**Markets (product-region pairs) are numbered in ascending order of the prior information proxy.*

where $CTR_{amt} \in [0,1]$ is the click-through rates of display ad a in market m on day t, $Q^{Display}_{amt} = 1$ if the display ad content a in market m on day t is quality-focused ($a \in \mathcal{Q}$) and 0 otherwise, and $\widehat{I}_m$ denotes a market-level proxy for prior information about product quality recovered in Section 3.3. The baseline condition is transactional-ease content, so heterogeneous CTRs under transactional-ease ads across markets are captured by $\beta_0 + \beta_2 \widehat{I}_m$.

Next, to test how the effect of quality-focused landing ad content relative to transactional-ease content varies with prior information and preceding display ad content, we run the following regression:

$$
\begin{aligned}
Y_{imt} = & \gamma_0 + \gamma_1 Q_{imt}^{Landing} + \gamma_2 \widehat{I}_m + \gamma_3 Q_{imt}^{Landing} \times \widehat{I}_m \\
& + \gamma_4 Q_{imt}^{Display} + \gamma_5 Q_{imt}^{Display} \times \widehat{I}_m \\
& + \gamma_6 Q_{imt}^{Landing} \times Q_{imt}^{Display} + \gamma_7 Q_{imt}^{Landing} \times Q_{imt}^{Display} \times \widehat{I}_m + \eta_{imt}
\end{aligned} \tag{9}
$$

where $Y_{imt} = 1$ if customer i (tracked by IP address) who lands at the website on day t in market m takes action and 0 otherwise, $Q_{imt}^{\text{Landing}} = 1$ if the landing ad content that customer i is exposed to is quality-focused and 0 otherwise, and $Q_{imt}^{\text{Display}} = 1$ if the preceding display ad content that customer i clicked on before arriving at the website is quality-focused and 0 otherwise.

Table 4 summarizes the hypothesis tests based on our empirical specification.

Table 4: Hypotheses testing

The role of ad content	Predictions about the effect of quality-focused content relative to transaction-focused content		
	Main effect within each period	Carryover effect on downstream action	Relationship between two contents
Informative	$\beta_3 < 0, \gamma_3 < 0$ (H1-1)	$\gamma_5 < 0$ (H1-2)	$\gamma_6 + \gamma_7 \widehat{I}_m < 0$ (H1-3)
Preference-matching	$\beta_3 = 0, \gamma_3 = 0$ (H2-1)	$\gamma_4 = \gamma_5 = 0$ (H2-2)	$\gamma_6 + \gamma_7 \widehat{I}_m > 0$ (H2-3)
Navigational	$\beta_1 = \beta_3 = 0,$ $\gamma_1 = \gamma_3 = 0$ (H3-1)	$\gamma_4 = \gamma_5 = 0$ (H3-2)	$\gamma_6 + \gamma_7 \widehat{I}_m = 0$ (H3-3)

Although not listed as a formal prediction, we leverage the empirical specification to test the following:

$$\gamma_7 \neq 0 \quad \Rightarrow \quad \text{Relationship between the two ads changes with prior information.} \quad \text{(H4)}$$

To assess whether vertical-quality and match-likelihood content within quality-focused ads lead to significantly different result, we re-estimate Equation (8) and (9) using H (a binary indicator for match-likelihood ads) and V (a binary indicator for vertical-quality ads) in place of Q in some of the specifications. As a robustness check, we re-estimate Equation (9) using product–country-specific prior information ($\widehat{I}_c$ in Figure 3(b)) instead of market-level prior information ($\widehat{I}_m$ in Figure 3(a)).

5 Results

5.1 Effects of Display Ad Headlines on Click-Through Rates

Table 5: Effect of Display Ad Content on CTR (Baseline: Transactional-Ease Content)

Dependent Variable:	CTR (in percentage points)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Constant	2.602	2.598		2.602	2.598	
	(0.1092)	(0.1109)		(0.1093)	(0.1109)	
	[< 0.001]	[< 0.001]		[< 0.001]	[< 0.001]	
Quality-focused display ad ($Q_{amt}^{Display}$)	0.0693	0.0881	0.0848			
	(0.0628)	(0.0316)	(0.0332)			
	[0.307]	[0.027]	[0.038]			
Prior information ($\widehat{I}_m$)		0.0226			0.0226	
		(0.0555)			(0.0555)	
		[0.696]			[0.696]	
$Q_{amt}^{Display} \times \widehat{I}_m$		-0.1456	-0.1492			
		(0.0185)	(0.0186)			
		[< 0.001]	[< 0.001]			
Quality-focused ad: Match likelihood ($H_{amt}^{Display}$)				0.0746	0.0924	0.0926
				(0.0587)	(0.0306)	(0.0310)
				[0.244]	[0.019]	[0.020]
Quality-focused ad: Vertical quality ($V_{amt}^{Display}$)				0.0640	0.0836	0.0767
				(0.0695)	(0.0377)	(0.0396)
				[0.388]	[0.062]	[0.094]
$H_{amt}^{Display} \times \widehat{I}_m$					-0.1328	-0.1358
					(0.0164)	(0.0163)
					[< 0.001]	[< 0.001]
$V_{amt}^{Display} \times \widehat{I}_m$					-0.1586	-0.1630
					(0.0279)	(0.0282)
					[0.001]	[0.001]
Market FE			Yes			Yes
Date FE			Yes			Yes
Observations	3,495	3,495	3,495	3,495	3,495	3,495
Adjusted R^2	0.00055	0.01218	0.07361	0.00029	0.01178	0.07331
Within Adjusted R^2			0.00408			0.00375

Clustered (market-level) standard-errors in parentheses and p-values in square brackets

Table 5 reports the regression results from the linear probability model in Equation 8.[14] In Column (1), when heterogeneity in ad content effects across markets is omitted,

[14] To reduce reliance on noisy CTR estimates when impression counts are low, we report estimation results from a weighted regression using impressions as weights.

the average effect of quality-focused display ad ($Q_{amt}^{Display}$) relative to transaction-focused ad is statistically insignificant. Distinguishing quality-focused ad content by two different types (match likelihood $H_{amt}^{Display}$ and vertical quality $V_{amt}^{Display}$) returns the same average null effects (Column (4)). However, when the interaction effects between content types and prior information $\widehat{I}_m$ is incorporated in in Column (2), it not only yields significant heterogeneous effects of quality-focused content on CTRs but also results in a notable increase in adjusted R^2. This suggests that, without allowing for heterogeneity in ad content effects across markets, one could reach a misleading conclusion that changing ad content from transaction-focused to quality-focused does not significantly affect ad clicks.

In Columns (2) and (3), we find evidence that display ad content functions as a meaningful source of information, consistent with H1-1. The interaction effect between quality-focused ad headlines and prior information (the coefficient of $Q_{amt}^{Display} \times \widehat{I}_m$; β_3 in Equation 8) is negative and statistically significant: the more prior information a market already has, the weaker the effect of quality-focused display ads on CTRs. This systematic negative relationship between prior information and quality-focused ad content indicates that customers actively process product quality information in the display ad, relying on it more when their prior knowledge is limited. The interaction effect stays robust with fixed effects (Column (3)). The coefficient of prior information $\widehat{I}_m$ (β_2 in Equation 8) is positive but statistically insignificant, indicating that variations in CTRs across markets exposed to transactional-ease display ads are not significantly correlated with market-level prior information.

The magnitudes of heterogeneous ad content effects across markets are economically significant, indicating that the most effective content varies widely across markets even for ads from the same company. For example, the coefficients in Column (6) indicate that in the market with the highest level of prior information (proxy = 1.604), replacing transaction-focused headlines with vertical-quality content reduces CTR by 0.186 percentage points ($= 0.0767 - 0.1639 \times 1.604$), corresponding to a 7.1% loss in CTR. By contrast, in the market with the lowest level of prior information (proxy = -1.140), the same changes in display ad headline result in 10.1% gain in CTR.

To ensure that the results are not driven by a few headlines as an outliers, we estimate the effect of display ad content on CTR by individual ad headline and market, having transactional ease headlines as the baseline:

$$CTR_{amt} = b_0^m + \sum_{k \in \mathcal{Q}} b_k^m \mathbb{1}\{a = k\} + \epsilon_{amt} \tag{10}$$

where $\mathbb{1}\{a = k\}$ is 1 if the display ad a features headline k among quality-focused headlines (Table 2). We estimate headline-specific coefficients for each individual market (b_k^m), with 32 coefficients in total (4 headlines excluding the baseline $\times$ 8 markets = 32 coefficients). Figure 5 plots the estimated coefficients (y-axis) against the prior information proxy (x-axis). The strong negative correlation indicates that markets with higher prior information exhibit lower relative effectiveness of quality-focused headlines on CTR, confirming that the negative interaction in Table 5 is not driven by a few outliers.

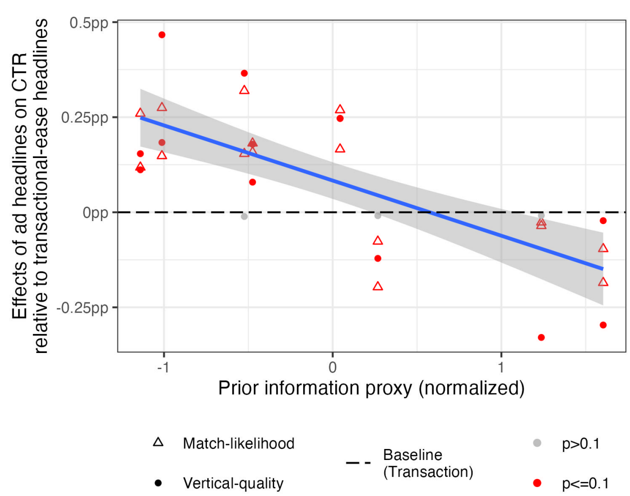


Figure 5: The effects of display ad headlines on CTR: Robustness check

The results show similar effect sizes of vertical-quality and match-likelihood content in low-information markets, indicating lack of information on both dimensions. When we decompose quality-focused ads into match-likelihood and vertical-quality ads in Columns (5) and (6), we find similar magnitudes for the main and interaction effects between prior information and each type of quality-focused content.[15] Although this suggests that customers respond similarly to both types of quality information at the display ad stage, it highlights the need for further analysis of their differential effects on downstream browsing behaviors conditional on clicking through the ad.

In summary, the experimental results underscore the heterogeneous effects of display ad content as a source of information in the B2B context. First, we observe substantial heterogeneity in ad effectiveness across markets, suggesting that the same headline generates varying responses depending on the product and geographic region. Second, this variation is strongly correlated with market-level prior information about the advertised product, proxied by the volume of direct searches in organic traffic. These findings suggest that strong prior knowledge substitutes for ad content related to product quality, underscoring the role of display ad content as a key information source even in B2B contexts where customers are typically considered information-savvy.

5.2 Effects of landing page ad and display ad headlines on downstream behavior

Next, we discuss the direct effect of landing page ad content on action rates, independent of interaction with display ad content. Table 6 reports the results from estimating Equation (9) using a linear probability model. As in Table 5, the average effect of quality-focused landing page ads ($Q_{imt}^{Landing}$), relative to transactional-ease content, is statistically insignificant (Column (1)). When we include the interaction between quality-focused landing page ads and the prior information proxy ($Q_{imt}^{Landing} \times \widehat{I}_m$) in Column (2), its coefficient is negative and statistically significant (-0.9395) while the main effect still remains insignificant. This finding supports H1-1, indicating that landing page ad content also serves as a source of information in our setting: the relative effectiveness of quality-focused content on the landing page in driving downstream actions declines as prior information increases. The results remain robust when controlling for fixed

[15] The coefficients of the two interaction terms, $H_{amt}^{Display} \times \hat{I}m$ and $V_{amt}^{Display} \times \hat{I}_m$, are not statistically different from each other ($\chi^2 = 1.013, ; p = 0.3141$ in Column (6)).

Table 6: Effects of Two Consecutive Ad Contents on Action Rates (Baseline: Transactional-Ease Content)

Dependent Variable:	$\mathbb{1}\{\text{Action within session}\} \times 100\%$			
Model:	(1)	(2)	(3)	(4)
Constant	1.202	1.591		
	(0.2921)	(0.4602)		
	[0.004]	[0.011]		
$Q_{imt}^{Landing}$ (Quality-focused landing page ad)	0.3295	-0.1655	-0.4995	0.3171
	(0.2167)	(0.4792)	(0.5758)	(0.4576)
	[0.172]	[0.740]	[0.414]	[0.511]
$Q_{imt}^{Display}$ (Quality-focused display ad)	0.1635	-0.3431	-0.1737	0.6027
	(0.2938)	(0.3535)	(0.3429)	(0.3592)
	[0.595]	[0.364]	[0.628]	[0.137]
$\widehat{I}_m$ (Prior information)		0.9100		
		(0.2728)		
		[0.013]		
$Q_{imt}^{Landing} \times Q_{imt}^{Display}$		0.6599	0.6286	0.0030
		(0.4706)	(0.4923)	(0.3647)
		[0.204]	[0.242]	[0.994]
$Q_{imt}^{Landing} \times \widehat{I}_m$		-0.9395	-1.100	
		(0.3143)	(0.3661)	
		[0.020]	[0.020]	
$Q_{imt}^{Display} \times \widehat{I}_m$		-0.9283	-1.042	
		(0.2349)	(0.2128)	
		[0.005]	[0.002]	
$Q_{imt}^{Landing} \times Q_{imt}^{Display} \times \widehat{I}_m$		0.6658	0.7947	
		(0.2957)	(0.2930)	
		[0.059]	[0.030]	
$Q_{imt}^{Landing} \times \widehat{I}_c$ (Product-country-level prior information)				-2.249
				(0.8417)
				[0.032]
$Q_{imt}^{Display} \times \widehat{I}_c$				-2.202
				(0.6925)
				[0.015]
$Q_{imt}^{Landing} \times Q_{imt}^{Display} \times \widehat{I}_c$				1.799
				(0.9415)
				[0.098]
Market(Product-Region)-Mobile session FE			Yes	
Product-Country-Mobile session FE				Yes
Date FE			Yes	Yes
Observations	13,576	13,576	13,576	13,482
Adjusted R^2	-0.00002	0.00019	0.00471	0.01260
Within Adjusted R^2			0.00011	0.00013

Clustered (market-level) standard-errors in parentheses and p-values in square brackets

The table reports results estimated with a linear probability model. A binary logit specification yields consistent findings.

effects (Column (3)) and when using a more granular prior information proxy at the product–country level (Column (4)).

We also observe significant carryover effects of display ad content on downstream action rates, consistent with the prediction under informative ad content (H1-2). In Column (2), the interaction between quality-focused display ad content and prior information ($Q_{imt}^{Display} \times \widehat{I}_m$) is negative and statistically significant (-0.9283), suggesting that the informational role of display ads extends beyond customers' ad click decisions to their downstream action. In other words, the gains in CTRs from display ads on product quality in low-information markets (documented in Section 5.1) are not offset by lower average action rates – contrary to common concerns about the trade-off between the total number and individual value of customers observed in marketing strategies. These results hold with fixed effects (Column (3)) and with the product-country-level prior information measure (Column (4)).

Finally, we examine the interaction between landing page ad and display ad content, exploring the relationship between the two across markets. The coefficient of $Q_{imt}^{Landing} \times Q_{imt}^{Display}$ (γ_6 in Equation 9) is statistically insignificant across all specifications, suggesting that the average relationship between the two consecutive quality-focused contents is close to independent. However, the coefficient of the three-way interaction $Q_{imt}^{Landing} \times Q_{imt}^{Display} \times \widehat{I}_m$ (γ_7 in Equation 9) is statistically significant, indicating that the relationship between consecutive product-quality ad contents is not fixed but varies with the level of prior information, as predicted in H4 in Section 4.

The changing relationship between the two consecutive ads as a function of prior information is illustrated in Figure 6, which plots the market-specific interaction effect between the two quality-focused ad contents (ϕ_3^m) estimated from the following regression:

$$Y_{imt} = \phi_0^m + \phi_1^m Q_{imt}^{Landing} + \phi_2^m Q_{imt}^{Display} + \phi_3^m Q_{imt}^{Landing} \times Q_{imt}^{Display} + \omega_{imt}. \tag{11}$$

In low-information markets (Markets 1 to 4 in Figure 6 with $\widehat{I}_m < 0$), the interaction effect between the two consecutive quality-focused ads is negative, indicating that the two contents are substitutable as predicted under the informative advertising framework (H1-3). In contrast, the interaction effect becomes positive in high-information markets (Markets 5 to 8 with $\widehat{I}_m > 0$), suggesting that the second exposure to the quality-focused content complements the first as predicted under the preference-matching advertising model (H2-3). To summarize, customers in low-information markets view consecutive quality-focused ads as substitutable sources of information, whereas customers in high-

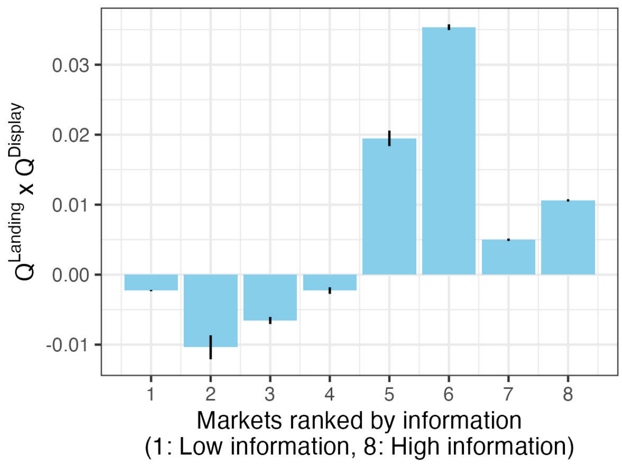


Figure 6: Ad interaction effects by market

The figure reports market-specific coefficients of $Q_{imt}^{Landing} \times Q_{imt}^{Display}$, estimated directly rather than through interaction with prior information $\widehat{I}$ using a linear probability model.

information markets interpret them as preference-confirming signals – responding more positively when both ads consistently speak to product quality.

Table 7 reports the regression results that further decompose quality-focused content into vertical-quality and match-likelihood ads. Although showing generally insignificant average effects, the two types of quality-focused content reveal distinct patterns in their individual effects across markets, suggesting that they operate through different underlying mechanisms. The effect of match-likelihood content on action rates is greater in low-information markets than in high-information markets and creates a significant carryover effect, indicated by the negative coefficients of $H_{imt}^{Landing} \times \widehat{I}_m$ and $H_{imt}^{Display} \times \widehat{I}_m$ (Columns (2) and (3)). The two consecutive match-likelihood contents work as substitutes in low-information markets, suggested by the insignificant coefficient of $H_{imt}^{Landing} \times H_{imt}^{Display}$ and the negative coefficient of $H_{imt}^{Landing} \times H_{imt}^{Display} \times \widehat{I}_m$. These patterns are consistent with H1-1, H1-2, and H-3 under the informative mechanism of advertising. In contrast, the effects of vertical-quality ads show much weaker correlations with the prior information proxy, with the coefficients of $V_{imt}^{Landing} \times \widehat{I}_m$ and $V_{imt}^{Display} \times \widehat{I}_m$ often statistically insignificant (Columns (2) and (3)). Furthermore, two consecutive vertical-quality ads are complementary on average (according to the significant and positive coefficient of $V_{imt}^{Landing} \times V_{imt}^{Display}$) without significant heterogeneity across prior information levels (ac-

Table 7: Effect of two ad contents on action rates with granular content classification (Baseline: transactional-ease content)

Dependent Variable:	$\mathbb{1}\{\text{Action within session}\} \times 100\%$		
Model:	(1)	(2)	(3)
Constant	1.206	1.591	
	(0.2924) [0.004]	(0.4604) [0.011]	
$\widehat{I}_m$		0.9100	
		(0.2729) [0.013]	
Individual effects			
$H_{imt}^{Landing}$	0.3412	-0.5341	-0.4670
	(0.2575) [0.227]	(0.4738) [0.297]	(0.5232) [0.402]
$H_{imt}^{Landing} \times \widehat{I}_m$		-1.330	-1.531
		(0.2514) [0.001]	(0.3131) [0.002]
$H_{imt}^{Display}$	0.3559	0.0644	0.2023
	(0.4168) [0.421]	(0.3947) [0.875]	(0.3784) [0.610]
$H_{imt}^{Display} \times \widehat{I}_m$		-1.384	-1.550
		(0.3149) [0.003]	(0.3027) [0.001]
$V_{imt}^{Landing}$	0.3096	-0.6781	-0.5531
	(0.2000) [0.166]	(0.6542) [0.335]	(0.6766) [0.441]
$V_{imt}^{Landing} \times \widehat{I}_m$		-0.5425	-0.7285
		(0.4417) [0.259]	(0.4887) [0.180]
$V_{imt}^{Display}$	-0.0258	-0.7222	-0.5256
	(0.2495) [0.921]	(0.3764) [0.097]	(0.3805) [0.210]
$V_{imt}^{Display} \times \widehat{I}_m$		-0.4856	-0.5447
		(0.2764) [0.122]	(0.2607) [0.075]
Joint effects			
$H_{imt}^{Landing} \times H_{imt}^{Display}$		0.5579	0.5220
		(0.5936) [0.379]	(0.6021) [0.415]
$H_{imt}^{Landing} \times V_{imt}^{Display}$		0.6700	0.6052
		(0.4044) [0.141]	(0.4376) [0.209]
$V_{imt}^{Landing} \times H_{imt}^{Display}$		0.3396	0.3150
		(0.7348) [0.658]	(0.7432) [0.684]
$V_{imt}^{Landing} \times V_{imt}^{Display}$		1.124	1.047
		(0.4382) [0.037]	(0.4429) [0.050]
$H_{imt}^{Landing} \times H_{imt}^{Display} \times \widehat{I}_m$		1.281	1.511
		(0.3631) [0.010]	(0.3861) [0.006]
$H_{imt}^{Landing} \times V_{imt}^{Display} \times \widehat{I}_m$		0.8367	0.8906
		(0.2596) [0.015]	(0.2838) [0.016]
$V_{imt}^{Landing} \times H_{imt}^{Display} \times \widehat{I}_m$		0.9288	1.142
		(0.5393) [0.129]	(0.5394) [0.072]
$V_{imt}^{Landing} \times V_{imt}^{Display} \times \widehat{I}_m$		-0.2738	-0.2295
		(0.2595) [0.326]	(0.2607) [0.408]
Market (Product-Region) FE			Yes
Date FE			Yes
Observations	13,576	13,576	13,576
Adjusted R^2	2.06×10^{-5}	0.00258	0.00475
Within Adjusted R^2			0.00015

Clustered (market-level) standard-errors in parentheses

The table reports results estimated with a linear probability model. A binary logit specification yields consistent findings. Using the product–country-level prior information proxy generates qualitatively similar results.

cording to the insignificant coefficient of $V_{imt}^{Landing} \times V_{imt}^{Display} \times \widehat{I}_m$). These pattern aligns more closely with the preference-matching mechanism (H2-1, H2-2, and H2-3). When match-likelihood and vertical-quality contents are mixed across the two placements, the relationship between the ads varies with prior information in a similar way to the case of two consecutive match-likelihood ads, though more weakly due to the presence of vertical-quality content.

In summary, we find that both landing page ad and display ad contents individually and jointly affect customers' downstream action. Low-information markets exhibit higher engagement under quality-focused content but treat two sequential messages on product quality (especially on match likelihood) as substitutes. In contrast, high-information markets engage more under transaction-focused content but treat sequential messages on quality (either match likelihood or vertical quality) as complements. This indicates that the joint effect of two sequential ad contents is shaped by the interaction between prior information and the sequence of those contents, underscoring the economic value of ad content coordination.

6 Economic value of ad content coordination

To assess the economic significance of ad content coordination given the heterogeneous relationships between the two consecutive contents across markets, we compare predicted outcomes for each market across five scenarios. Scenario 1 reflects a business-as-usual approach, with both display and landing page ads being transaction-focused across all markets. Scenario 2 assumes that ad headlines are randomly assigned among three content types (transactional ease, match likelihood, vertical quality) across markets. Scenario 3 applies the CTR-maximizing display ad content while maintaining business-as-usual landing page content (transactional ease). Scenario 4 keeps the display ad content fixed to be business-as-usual (transactional ease) while manipulating only the landing page headlines to achieve highest action rates. In the Best scenario, we implement the action-rate-maximizing combination of display ads and landing play ads. To generate predictions, we use predicted click-through rates and action rates from Equations (8) and (9) to obtain market-specific click-through and action rates under each scenario s.

As a robustness check, Section D.2 in the Appendix shows the prediction results under the assumption of discrete heterogeneity in ad content effects across markets.

We focus on total clicks, total actions, and cost per action as the main outcomes for comparison:

$$TotalClicks^{(s)} = \sum_m M_m \times \overline{CTR}_m^{(s)}, \quad TotalActions^{(s)} = \sum_m M_m \times \overline{CTR}_m^{(s)} \times \overline{Y}_m^{(s)},$$

$$CostPerAction^{(s)} = \sum_m \frac{M_m \times c_m}{M_m \times \overline{CTR}_m^{(s)} \times \overline{Y}_m^{(s)}}$$

where M_m denotes market-specific average impressions, $\overline{CTR}_m^{(s)}$ is the predicted average click-through rate in market m under scenario s, $\overline{Y}_m^{(s)}$ is the predicted average action rate, and c_m represents the cost per impression which varies across regions based on proprietary data. This approach allows us to compare predicted clicks and downstream actions while holding impressions fixed across all scenarios. To construct standard errors for predicted outcomes, we apply bootstrapping with 1,000 random resamples of the observed data.

Table 8: Predicted ad content coordination across markets

Ad sequence (Display × Landing page)	Scenario 1 (Business-as-usual)	Scenario 2 (Random display)	Scenario 3 (Display ad only)	Scenario 4 (Landing page ad only)	Best
D×D	100%	12%	24%	37%	23%
D×H	0%	10%	0%	44%	4%
D×V	0%	11%	0%	20%	4%
H×D	0%	13%	43%	0%	16%
H×H	0%	11%	0%	0%	36%
H×V	0%	10%	0%	0%	6%
V×D	0%	12%	34%	0%	1%
V×H	0%	11%	0%	0%	1%
V×V	0%	10%	0%	0%	9%

The table shows the frequency of each ad sequence appearing across eight markets under the five scenarios. In the ad sequences, D denotes content about transactional ease, H denotes content about horizontal match likelihood, and V denotes content about vertical quality.

Table 8 summarizes the distribution of predicted ad sequences under the five scenarios. In Scenario 1, $D \times D$ (transactional-ease content D in both display ad and landing page ad) appears in 100% of markets across all bootstrapped samples, reflecting the business-as-usual case in which both display and landing page ads are transaction-focused. In Scenario 3, all sequences that do not include D in the landing page ad have zero appearances as only transaction-focused ads are used in the landing page under this scenario, leaving three possible sequences with non-zero representation ($D \times D$, $H \times D$, $V \times D$). Similarly, in Scenario 4, all sequences excluding D in the display ad have zero appearances as only transaction-focused ads are used in the display ad, again leaving three sequences with non-zero representation ($D \times D$, $D \times H$, $D \times V$). In both Scenarios 3 and 4, ad sequences are distributed relatively evenly across the possible three cases, confirming that the content types that maximize CTR and action rates vary substantially across markets.[16] In the Best scenario, the selected ad sequences are also widely dispersed, indicating that no single sequence dominates. This dispersion reflects the interaction effects of the two ad contents – which vary systematically with prior information and content type – in addition to the heterogeneous effects of individual ad content.

Table 9: Predicted customer engagement relative to Scenario 1 (business-as-usual)

Scenario	Total ad clicks	Total actions	Cost per action
Scenario 2 (Random display)	2.06% [0.03, 4.25]	-3.26% [-40.29, 73.97]	11.40% [-42.52, 67.47]
Scenario 3 (Display ad only)	4.95% [2.53, 7.84]	21.83% [-35.57, 134.23]	-9.35% [-57.31, 55.20]
Scenario 4 (Landing page ad only)	0%	25.98% [-7.74, 108.57]	-16.77% [-52.05, 8.39]
Best	3.93% [0.50, 7.23]	69.21% [9.29, 192.63]	-37.19% [-65.83, -8.50]

The table shows market outcomes under different scenarios relative to Scenario 1 (business-as-usual). 95% confidence intervals, shown in square brackets, are based on the 2.5th and 97.5th percentiles of the bootstrap distribution.

Table 9 reports predicted outcomes relative to Scenario 1 (business-as-usual). Randomly assigning ad content across the two placements yields a higher number of clicks on average, but reduces total actions and increases cost per action on average. Both Scenario 3 and Scenario 4 lead to increases in total actions and reductions in cost per action on average, with wide 95% confidence intervals that overlap with zero. The magnitudes of average gains in actions are comparable across Scenarios 3 and 4, suggesting that each ad placement independently contributes to facilitating online customer engagement. We

[16] Splitting the table into low-information and high-information markets reveals a systematic correlation between engagement-maximizing content types and prior information, which is otherwise obscured by the seemingly even distribution of ad sequences (see Table D.1)

draw two implications from these. First, landing page ad content remains an effective lever for online customer acquisition even when display ads are not optimized to attract high-preference customers. Second, in our setting, display ad content that maximizes click-through rates also increases action rates and lowers cost per action on average – consistent with the significant carryover effects documented in Table 6 (Section 5.2).

When display and landing page ad contents are coordinated to maximize action rates under the Best scenario, total actions rise by 69.21% and cost per action falls by 37.19% on average relative to the business-as-usual scenario, with 95% confidence intervals not overlapping with zero. The incremental actions generated over a four-month period under the Best scenario correspond to approximately 19.9% of all actions observed from display-ad–initiated traffic in 2022. The magnitude of the improvement in both actions and costs exceeds the sum of average gains from Scenarios 3 and 4, underscoring the substantial economic value of coordinated ad content across sequential placements.

The marked increases in ad clicks and downstream actions driven by market-level content design highlight a privacy-friendly avenue for improving ad performance. Regulations such as GDPR, together with limited data on first-time visitors, increasingly constrain individual-level targeting. Our findings demonstrate a high-return strategy for enhancing ad effectiveness within prevailing privacy and data limitations.

7 Conclusion

Using a field experiment in a B2B setting, we provide experimental evidence that two sequential online ad contents – display ad and landing page ad contents – have a substantial joint impact on click-through rates and downstream actions. Low-information markets exhibit higher engagement under quality-focused content but treat two sequential messages on product quality as substitutes. In contrast, high-information markets engage more under transaction-focused content but treat sequential messages on quality as complements. We relate these patterns to theoretical perspectives on the role of advertising – as an information source, a preference-matching device, and a navigational shortcut – and highlight the economic significance of ad content coordination through prediction exercises. Our findings also imply information frictions and high search costs in B2B markets, underscoring the critical role of B2B advertising in addressing these frictions - an advertising industry worth $21 billion that is often overlooked in the literature due to assumptions of more informed and rational customers. They also shed light on considerable heterogeneity in ad content effects across markets, which can be masked by average null effects.

Our findings offer marketers a practical strategy for improving online customer acquisition. Markets with low non-ad-initiated named searches (low information) benefit more from ad headlines featuring product quality, while high-search (high-information) markets respond better to headlines highlighting transactional ease. In our setting, match-likelihood headlines are likely to meet informational needs in low-information environments, while vertical-quality headlines work more as attracting customers with specific preferences in high-information environments. Our approach addresses privacy concerns and the lack of data on first-time customers by leveraging aggregate information, helping to alleviate the cold start problem in customer relationship management.

Our study has several limitations. The experimental design does not allow us to make a direct comparison between ad exposure effects and ad content effects. For example, as our analyses are conditional on both display ad and landing page ad exposures, we are unable to assess the value of turning on landing page ads. We do not employ multiple variations of transaction-focused ad headlines or test the effects across different contexts such as B2C settings. We leave it to future research to explore the generalizability of our results across different contexts and headline variations.

References

Ackerberg, D. A. (2001). Empirically distinguishing informative and prestige effects of advertising. *RAND Journal of Economics*, 316–333.

Ackerberg, D. A. (2003). Advertising, learning, and consumer choice in experience good markets: An empirical examination. *International Economic Review*, *44*(3), 1007–1040.

Bagwell, K. (2007). The economic analysis of advertising. *Handbook of industrial organization*, *3*, 1701–1844.

Banerjee, A., & Urminsky, O. (2024). The language that drives engagement: A systematic large-scale analysis of headline experiments. *Marketing Science*.

Biswas, S. (2020). *Investigating the effects of including discount information in advertising*. The University of Chicago.

Blake, T., Nosko, C., & Tadelis, S. (2015). Consumer heterogeneity and paid search effectiveness: A large-scale field experiment. *Econometrica*, *83*(1), 155–174.

Broder, A. (2002). A taxonomy of web search. *ACM Sigir forum*, *36*(2), 3–10.

Bruce, N. I., Murthi, B., & Rao, R. C. (2017). A dynamic model for digital advertising: The effects of creative format, message content, and targeting on engagement. *Journal of marketing research*, *54*(2), 202–218.

Dotson, J. P., Fan, R. R., Feit, E. M., Oldham, J. D., & Yeh, Y.-H. (2017). Brand attitudes and search engine queries. *Journal of Interactive Marketing*, *37*(1), 105–116.

eMarketer. (2024). Business-to-business (b2b) digital advertising spending in the united states from 2022 to 2026 (in billion u.s. dollars) [graph] [Retrieved June 18, 2025, from Statista].

Erdem, T., & Keane, M. P. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science*, *15*(1), 1–20. https://doi.org/10.1287/mksc.15.1.1

Fisher, M. L., Gallino, S., & Xu, J. J. (2019). The value of rapid delivery in omnichannel retailing. *Journal of Marketing Research*, *56*(5), 732–748.

Gordon, B. R., Zettelmeyer, F., Bhargava, N., & Chapsky, D. (2019). A comparison of approaches to advertising measurement: Evidence from big field experiments at facebook. *Marketing Science*, *38*(2), 193–225. https://doi.org/10.1287/mksc.2018.1135

Gui, G., & Drerup, T. H. (2022). Designing promises with reference-dependent customers: The case of online grocery delivery time. *Working Paper*.

Guitart, I. A., & Stremersch, S. (2021). The impact of informational and emotional television ad content on online search and sales. *Journal of Marketing Research*, *58*(2), 299–320.

Hauser, J. R., Urban, G. L., Liberali, G., & Braun, M. (2009). Website morphing. *Marketing Science*, *28*(2), 202–223.

Hoban, P. R., & Bucklin, R. E. (2015). Effects of internet display advertising in the purchase funnel: Model-based insights from a randomized field experiment. *Journal of Marketing Research*, *52*(3), 375–393.

Honka, E., Hortaçsu, A., & Vitorino, M. A. (2017). Advertising, consumer awareness, and choice: Evidence from the us banking industry. *The RAND Journal of Economics*, *48*(3), 611–646.

Honka, E., Seiler, S., & Ursu, R. (2024). Consumer search: What can we learn from pre-purchase data? *Journal of Retailing*, *100*(1), 114–129.

Lee, D., Hosanagar, K., & Nair, H. S. (2018). Advertising content and consumer engagement on social media: Evidence from facebook. *Management Science*, *64*(11), 5105–5131.

Liaukonyte, J., Teixeira, T., & Wilbur, K. C. (2015). Television advertising and online shopping. *Marketing Science*, *34*(3), 311–330.

Milgrom, P., & Roberts, J. (1986). Price and advertising signals of product quality. *Journal of political economy*, *94*(4), 796–821.

Morozov, I., & Tuchman, A. (2024). Where does advertising content lead you? we created a bookstore to find out. *Marketing Science*. https://doi.org/10.1287/mksc.2023.0138

Narayanan, S., & Kalyanam, K. (2015). Position effects in search advertising and their moderators: A regression discontinuity approach. *Marketing Science*, *34*(3), 388–407.

Nelson, P. (1974). Advertising as information. *Journal of political economy*, *82*(4), 729–754.

Padilla, N., & Ascarza, E. (2021). Overcoming the cold start problem of customer relationship management using a probabilistic machine learning approach. *Journal of Marketing Research*, *58*(5), 981–1006. https://doi.org/10.1177/00222437211032938

Rafieian, O. (2023). Optimizing user engagement through adaptive ad sequencing. *Marketing Science*, *42*(5), 910–933. https://doi.org/10.1287/mksc.2022.1423

Rafieian, O., & Yoganarasimhan, H. (2022). Variety effects in mobile advertising. *Journal of Marketing Research*, *59*(4), 718–738. https://doi.org/10.1177/00222437211056090

Rutz, O. J., & Bucklin, R. E. (2011). From generic to branded: A model of spillover in paid search advertising. *Journal of Marketing Research*, *48*(1), 87–102.

Sahni, N. S., & Nair, H. S. (2019). Does Advertising Serve as a Signal? Evidence from a Field Experiment in Mobile Search. *The Review of Economic Studies*, *87*(3), 1529–1564.

Sahni, N. S., Narayanan, S., & Kalyanam, K. (2019). An experimental investigation of the effects of retargeted advertising: The role of frequency and timing. *Journal of Marketing Research*, *56*(3), 401–418.

Seiler, S., & Yao, S. (2017). The impact of advertising along the conversion funnel. *Quantitative Marketing and Economics*, *15*, 241–278.

Sethuraman, R., Tellis, G. J., & Briesch, R. A. (2011). How well does advertising work? generalizations from meta-analysis of brand advertising elasticities. *Journal of marketing research*, *48*(3), 457–471.

Sudhir, K., Roy, S., & Cherian, M. (2016). Do sympathy biases induce charitable giving? the effects of advertising content. *Marketing Science*, *35*(6), 849–869.

Thomas, M., Goic, M., & Kalyanam, K. (2023). Advertising to businesses: Experimental evidence for high-involvement purchases. *Available at SSRN 4500501*.

Tounekti, O., Ruiz-Martínez, A., & Gómez, A. F. S. (2019). Users supporting multiple (mobile) electronic payment systems in online purchases: An empirical study of their payment transaction preferences. *IEEE access*, *8*, 735–766.

TrustRadius, P. (2024). *2024 b2b buying disconnect: The year of the brand crisis*. TrustRadius, Pavilion.

Tsai, Y.-L., & Honka, E. (2021). Informational and noninformational advertising content. *Marketing Science*, *40*(6), 1030–1058.

Ursu, R., Erdem, T., Wang, Q., & Zhang, Q. P. (2022). Prior information and consumer search: Evidence from eye-tracking. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4113480

Wang, Y., Banerjee, C., Chucri, S., Soldo, F., Badam, S., Chi, E. H., & Chen, M. (2024). Diversifying by intent in recommender systems. *arXiv preprint arXiv:2405.12327*.

Appendix

A Conceptual Framework: Proofs of Propositions

Proposition 1 (Informative Ad Contents). H1-1

$$
\begin{aligned}
\Phi_1(\mathcal{Q}) =& E[U_{ij1}(\mathcal{Q}) - U_{ij1}(\mathcal{D})] \\
=& \left(1 - \frac{\lambda_\tau}{\lambda_{ijq0} + \lambda_\tau}\right) \cdot \overline{q}_{ij0} + \left(\frac{\lambda_\tau}{\lambda_{ijq0} + \lambda_\tau}\right) \cdot \overline{\tau}_q + \overline{d}_{ij0} \\
& - \overline{q}_{ij0} - \left(1 - \frac{\lambda_\tau}{\lambda_{ijd0} + \lambda_\tau}\right) \cdot \overline{d}_{ij0} - \left(\frac{\lambda_\tau}{\lambda_{ijd0} + \lambda_\tau}\right) \cdot \overline{\tau}_d \\
=& \left(\frac{\lambda_\tau}{\lambda_{ijq0} + \lambda_\tau}\right) \cdot \underbrace{(\overline{\tau}_q - \overline{q}_{ij0})}_{\geq 0\ (\because \text{ Assumption 2})} - \left(\frac{\lambda_\tau}{\lambda_{ijd0} + \lambda_\tau}\right) \cdot (\overline{\tau}_d - \overline{d}_{ij0}) \\
& \therefore \frac{\partial \Phi_1(\mathcal{Q})}{\partial \lambda_{ijq0}} < 0 \\
\Phi_2(\mathcal{Q}|\mathcal{A}) =& E[U_{ij2}(\mathcal{Q}|\mathcal{A}) - U_{ij2}(\mathcal{D}|\mathcal{A})] \\
=& \left(1 - \frac{\lambda_\tau}{\lambda_{ijq1} + \lambda_\tau}\right) \cdot \overline{q}_{ij1} + \left(\frac{\lambda_\tau}{\lambda_{ijq1} + \lambda_\tau}\right) \cdot \overline{\tau}_q + \overline{d}_{ij1} \\
& - \overline{q}_{ij1} - \left(1 - \frac{\lambda_\tau}{\lambda_{ijd1} + \lambda_\tau}\right) \cdot \overline{d}_{ij1} - \left(\frac{\lambda_\tau}{\lambda_{ijd1} + \lambda_\tau}\right) \cdot \overline{\tau}_d \\
=& \left(\frac{\lambda_\tau}{\lambda_{ijq1} + \lambda_\tau}\right) \cdot \underbrace{(\overline{\tau}_q - \overline{q}_{ij1})}_{\geq 0\ (\because \text{ Assumption 2})} - \left(\frac{\lambda_\tau}{\lambda_{ijd1} + \lambda_\tau}\right) \cdot (\overline{\tau}_d - \overline{d}_{ij1}) \\
& \frac{\partial \Phi_2(\mathcal{Q}|\mathcal{A})}{\partial \lambda_{ijq1}} < 0, \frac{\lambda_{ijq1}}{\lambda_{ijq0}} > 0 \\
& \therefore \ \frac{\partial \Phi_2(\mathcal{Q}|\mathcal{A})}{\partial \lambda_{ijq0}} < 0
\end{aligned}
$$

Proposition 1 (Informative Ad Contents). H1-2 We would like to show that $\frac{\partial}{\partial \lambda_{iq0}} E[U_{ij2}(\mathcal{Q}|\mathcal{Q})] < 0$ and $\frac{\partial}{\partial \lambda_{iq0}} E[U_{ij2}(\mathcal{D}|\mathcal{Q})] < 0$.

$$
\begin{aligned}
E[U_{ij2}(\mathcal{Q}|\mathcal{Q})] =& \left(\frac{\lambda_\tau}{\lambda_{ijq1} + \lambda_\tau}\right) \cdot (\overline{\tau}_q - \overline{q}_{ij1}) + \overline{q}_{ij1} + \overline{d}_{ij0} \\
& \text{where } \overline{q}_{ij1} = \left(\frac{\lambda_\tau}{\lambda_{ijq0} + \lambda_\tau}\right) \cdot (\overline{\tau}_q - \overline{q}_{ij0}) + \overline{q}_{ij0} \text{ and } \lambda_{ijq1} = \lambda_{ijq0} + \lambda_\tau \\
E[U_{ij2}(\mathcal{Q}|\mathcal{Q})] =& \left(\frac{\lambda_\tau}{\lambda_{ijq0} + \lambda_\tau}\right) \cdot (\overline{\tau}_q - \overline{q}_{ij0}) + \overline{q}_{ij0} + \left(\frac{\lambda_\tau}{\lambda_{ijd0} + \lambda_\tau}\right) \cdot (\overline{\tau}_d - \overline{d}_{ij0}) + \overline{d}_{ij0}
\end{aligned}
$$

Proposition 1 (Informative Ad Contents). H1-3 Using the notations from H1-1, we would like to show that $\Phi_2(\mathcal{Q}|\mathcal{D}) > \Phi_2(\mathcal{Q}|\mathcal{Q})$.

$$\Phi_2(\mathcal{Q}|\mathcal{D}) = \left(\frac{\lambda_\tau}{\lambda_{ijq0} + \lambda_\tau}\right) \cdot (\overline{\tau}_q - \overline{q}_{ij0}) - \left(\frac{\lambda_\tau}{\lambda_{ijd1} + \lambda_\tau}\right) (\overline{\tau}_d - \overline{d}_{ij1})$$
$$\text{where } \overline{d}_{ij1} = \left(\frac{\lambda_\tau}{\lambda_{ijd0} + \lambda_\tau}\right) \cdot (\overline{\tau}_d - \overline{d}_{ij0}) + \overline{d}_{ij0} \text{ and } \lambda_{ijd1} = \lambda_{ijd0} + \lambda_\tau$$
$$\Phi_2(\mathcal{Q}|\mathcal{Q}) = \left(\frac{\lambda_\tau}{\lambda_{ijq1} + \lambda_\tau}\right) \cdot (\overline{\tau}_q - \overline{q}_{ij1}) - \left(\frac{\lambda_\tau}{\lambda_{ijd0} + \lambda_\tau}\right) (\overline{\tau}_d - \overline{d}_{ij0})$$
$$\text{where } \overline{q}_{ij1} = \left(\frac{\lambda_\tau}{\lambda_{ijq0} + \lambda_\tau}\right) \cdot (\overline{\tau}_q - \overline{q}_{ij0}) + \overline{q}_{ij0} \text{ and } \lambda_{ijq1} = \lambda_{ijq0} + \lambda_\tau$$

$$\lambda_{ijq1} > \lambda_{ijq0} \text{ and } \overline{q}_{ij1} > \overline{q}_{ij0} \quad (\because \text{ Assumptions 1, 2})$$
$$\Rightarrow \left(\frac{\lambda_\tau}{\lambda_{ijq1} + \lambda_\tau}\right) \cdot (\overline{\tau}_q - \overline{q}_{ij1}) < \left(\frac{\lambda_\tau}{\lambda_{ijq0} + \lambda_\tau}\right) \cdot (\overline{\tau}_q - \overline{q}_{ij0})$$
$$\lambda_{ijd1} > \lambda_{ijd0} \text{ and } d_{ij1} > d_{ij0} \quad (\because \text{ Assumptions 1, 2})$$
$$\Rightarrow \left(\frac{\lambda_\tau}{\lambda_{ijd1} + \lambda_\tau}\right) \cdot (\overline{\tau}_d - \overline{d}_{ij1}) < \left(\frac{\lambda_\tau}{\lambda_{ijd0} + \lambda_\tau}\right) \cdot (\overline{\tau}_d - \overline{d}_{ij0})$$
$$\therefore \quad \Phi_2(\mathcal{Q}|\mathcal{D}) - \Phi_2(\mathcal{Q}|\mathcal{Q}) > 0$$

Proposition 2 (Preference-matching Ad Contents). H2-1 The assumption that the preference-matching role of ad content dominates the informational role implies that $q_{ijt}(\mathcal{Q}) \approx q_{ijt}(\mathcal{D}) \approx q_{ij}$ and $d_{ijt}(\mathcal{Q}) \approx d_{ijt}(\mathcal{D}) \approx d_{ij}$ $\forall t$.

$$\Phi_1(\mathcal{Q}) = E[U_{ij1}(\mathcal{Q}) - U_{ij1}(\mathcal{D})] = \rho_{iq} - \rho_{id}$$

As ρ_{iq} and ρ_{id} are not functions of prior information by definition, they are orthogonal to the precision of the prior belief: $\frac{\partial}{\partial \lambda_{ijq0}}(\rho_{iq} - \rho_{id}) = 0$.

$$\Phi_2(\mathcal{Q}|\mathcal{A}) = E[\rho_{iq} - \rho_{id} | U_{ij1}(\mathcal{A}) > 0]$$

By definition, ρ_{iq} and ρ_{id} are not functions of prior information, so $\frac{\partial}{\partial \lambda_{ijq0}} E[\rho_{iq} - \rho_{id} | U_{ij1}(\mathcal{A}) > 0] = 0$.

Proposition 2 (Preference-matching Ad Contents). H2-2 This hypothesis follows directly from the utility specification in Equation (3), which assumes that the preference-matching parameters ρ_{iq} and ρ_{id} from Period 1 do not enter the Period 2 utility function.

Proposition 2 (Preference-matching Ad Contents). H2-3 Using the notation above, we would like to show that $\Phi_2(\mathcal{Q}|\mathcal{D}) - \Phi_2(\mathcal{Q}|\mathcal{Q}) < 0$.

$$\Phi_2(\mathcal{Q}|\mathcal{D}) = E[\rho_{iq} - \rho_{id} | U_{ij1}(\mathcal{D}) > 0] = E[\rho_{iq} - \rho_{id} | q_{ij} + d_{ij} + \rho_{id} > 0]$$

$$E[\rho_{iq} | q_{ij} + d_{ij} + \rho_{id} > 0] = E[\rho_{iq}] \quad (\because \text{Assumption 3})$$

$$E[\rho_{id} | q_{ij} + d_{ij} + \rho_{id} > 0] = E[\rho_{id} | \rho_{id} > -q_{ij} - d_{ij}] > E[\rho_{id}]$$

$$\Phi_2(\mathcal{Q}|\mathcal{Q}) = E[\rho_{iq} - \rho_{id} | U_{ij1}(\mathcal{Q}) > 0] = E[\rho_{iq} - \rho_{id} | q_{ij} + d_{ij} + \rho_{iq} > 0]$$

$$E[\rho_{iq} | q_{ij} + d_{ij} + \rho_{iq} > 0] = E[\rho_{iq} | \rho_{iq} > -q_{ij} - d_{ij}] > E[\rho_{iq}]$$

$$E[\rho_{id} | q_{ij} + d_{ij} + \rho_{iq} > 0] = E[\rho_{id}] \quad (\because \text{Assumption 3})$$

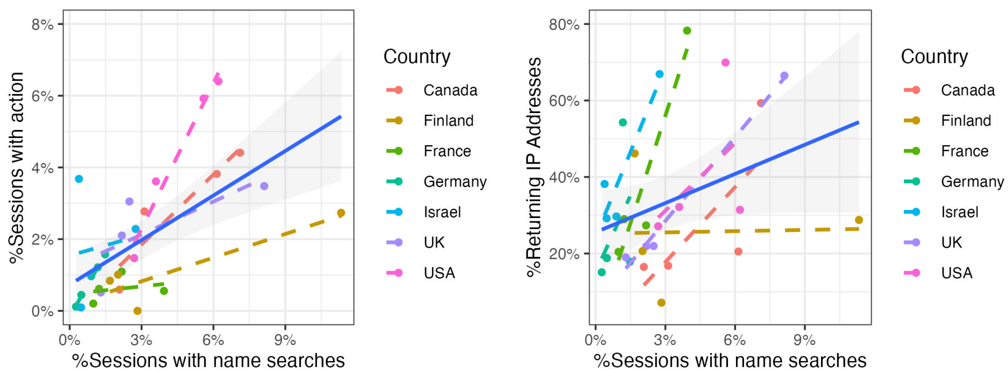
$$\therefore \quad \Phi_2(\mathcal{Q}|\mathcal{D}) - \Phi_2(\mathcal{Q}|\mathcal{Q}) = E[\rho_{iq}] - E[\rho_{id} | q_{ij} + d_{ij} + \rho_{id} > 0] - E[\rho_{iq} | \rho_{iq} > -q_{ij} - d_{ij}] + E[\rho_{id}]$$

$$= \underbrace{(E[\rho_{iq}] - E[\rho_{iq} | \rho_{iq} > -q_{ij} - d_{ij}])}_{<0} + \underbrace{(E[\rho_{id}] - E[\rho_{id} | q_{ij} + d_{ij} + \rho_{id} > 0])}_{<0} < 0.$$

B Inferring Prior Information from Pre-Experiment Data

B.1 Robustness Check

We interpret the measure of direct searches as a proxy of prior information about the advertised product's quality, whether that information pertains to vertical quality, match likelihood, or both. For an online customer to actively search for product names organically, they must already possess some knowledge about the product or company. To validate this interpretation, we compare it with several additional indicators that are likely to correlate with customers' prior knowledge.



(a) Within-session action rates

(b) % Returning IPs

Figure B.1: Comparison of name searches with other variables

First, we compare this measure with the likelihood of actions (e.g., sample orders, contacting sales) occurring within an organic session. We expect the within-session action rate to be positively correlated with customers' prior information about the product (and thus positively correlated with direct searches), as low amount of information typically prompts customers to search more and compare it with other options before taking action. As shown in Figure B.1(a), the direct searches exhibit a strong positive correlation with within-session action rates, reinforcing the validity of name searches as a measure of customers' prior information amount.

Second, we compare our proxy with the share of returning IP addresses in pre-experiment organic traffic. A high share of returning IPs indicates that most visitors have previously accessed the website, reflecting a greater amount of average prior information among the web traffic. Consistent with this expectation, our proxy is positively correlated with the share of returning IP addresses (Figure B.1(b)).

C Experimental results

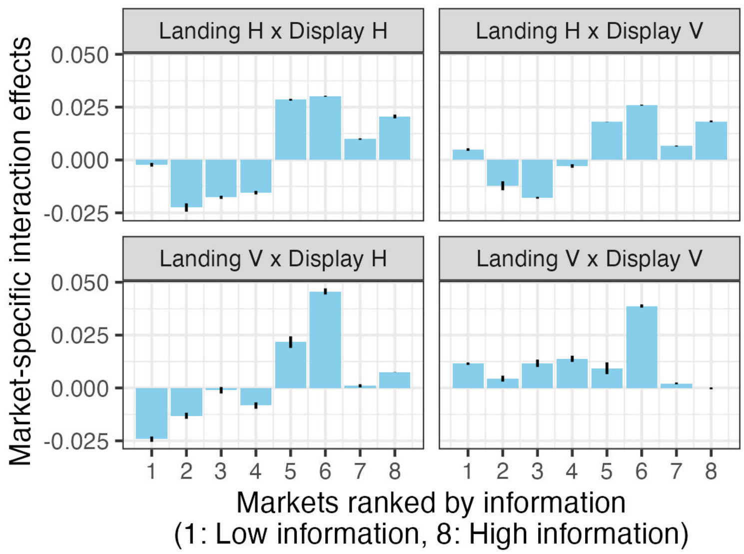


Figure C.1: Ad interaction effects by market: Match-Likelihood vs. Vertical-Quality

The figure reports market-specific interaction effects between two consecutive ad contents, estimated directly rather than through interaction with prior information $\widehat{I}$ using a linear probability model.

D Prediction exercises

D.1 Supplementary results

Table D.1: Predicted ad content coordination: By prior information

(a) In low-information markets

Ad sequence (Display × Landing page)	Scenario 1 (Business-as-usual)	Scenario 2 (Random display)	Scenario 3 (Display ad only)	Scenario 4 (Landing page ad only)	Best
D×D	100	12	0%	15%	1%
D×H	0%	10%	0%	75%	6%
D×V	0%	11%	0%	10%	0%
H×D	0%	13%	46%	0%	28%
H×H	0%	11%	0%	0%	45%
H×V	0%	10%	0%	0%	4%
V×D	0%	12%	54%	0%	0%
V×H	0%	11%	0%	0%	1%
V×V	0%	10%	0%	0%	14%

(b) In high-information markets

Ad sequence (Display × Landing page)	Scenario 1 (Business-as-usual)	Scenario 2 (Random display)	Scenario 3 (Display ad only)	Scenario 4 (Landing page ad only)	Best
D×D	100%	12%	47%	59%	45%
D×H	0%	10%	0%	12%	1%
D×V	0%	11%	0%	29%	8%
H×D	0%	13%	39%	0%	4%
H×H	0%	11%	0%	0%	28%
H×V	0%	10%	0%	0%	8%
V×D	0%	12%	13%	0%	3%
V×H	0%	11%	0%	0%	1%
V×V	0%	10%	0%	0%	3%

The tables show the frequency of each ad sequence appearing in four low-information markets and four high-information markets under the five scenarios. In the ad sequences, D denotes content about transactional ease, H denotes content about horizontal match likelihood, and V denotes content about vertical quality.

D.2 Prediction under discrete heterogeneity assumptions

While specifying ad content effects as a function of continuous prior information proxy as in Equations 8 and 9 helps identify the mechanisms underlying ad content effectiveness, estimating market-specific ad content effects in a discrete manner can provide a more flexible approach for prediction. As a robustness check, we estimate the following regressions with discrete content type-market-level heterogeneity in ad effects to obtain market-specific click-through and action rates under each scenario s:

$$CTR_{amt}^{(s)} = \delta_0^m + \delta_h^m H_{amt}^{Display}(s) + \delta_v^m V_{amt}^{Display}(s) + \iota_{amt} \tag{D.1}$$

$$\begin{aligned} Y_{imt}^{(s)} =& \rho_0^m + \rho_{h1}^m H_{imt}^{Landing}(s) + \rho_{v1}^m V_{imt}^{Landing}(s) + \rho_{h2}^m H_{imt}^{Display}(s) + \rho_{v2}^m V_{imt}^{Display}(s) \\ &+ \rho_{hh}^m H_{imt}^{Landing}(s) \times H_{imt}^{Display}(s) + \rho_{hv}^m H_{imt}^{Landing}(s) \times V_{imt}^{Display}(s) \\ &+ \rho_{vh}^m V_{imt}^{Landing}(s) \times H_{imt}^{Display}(s) + \rho_{vv}^m V_{imt}^{Landing}(s) \times V_{imt}^{Display}(s) + \zeta_{imt} \end{aligned} \tag{D.2}$$

where $H(s)$ and $V(s)$ are binary indicators for the assigned ad content, with $H(s) = 0$ and $V(s) = 0$ denoting the baseline transactional-ease content.

Tables D.2 and D.3 report the prediction outcomes under these alternative specifications. The results remain qualitatively and quantitatively similar to those presented in Section 6, reinforcing the robustness of our findings.

Table D.2: Predicted ad content coordination across markets

Ad sequence (Display × Landing page)	Scenario 1 (Business-as-usual)	Scenario 2 (Random display)	Scenario 3 (Display ad only)	Scenario 4 (Landing page ad only)	Best
D×D	100%	11%	29%	38%	20%
D×H	0%	12%	0%	37%	16%
D×V	0%	11%	0%	25%	8%
H×D	0%	12%	37%	0%	16%
H×H	0%	11%	0%	0%	16%
H×V	0%	10%	0%	0%	6%
V×D	0%	12%	34%	0%	4%
V×H	0%	10%	0%	0%	3%
V×V	0%	10%	0%	0%	10%

The table shows the frequency of each ad sequence appearing across eight markets under the five scenarios. In the ad sequences, D denotes content about transactional ease, H denotes content about horizontal match likelihood, and V denotes content about vertical quality.

Table D.3: Predicted customer engagement relative to Scenario 1 (business-as-usual)

Scenario	Total ad clicks	Total actions	Cost per action
Scenario 2 (Random content)	2.01% [-0.13, 4.34]	-6.75% [-34.89, 56.59]	12.53% [-36.14, 53.59]
Scenario 3 (Display ad only)	6.44% [3.67, 9.53]	6.40% [-3.74, 23.37]	-5.66% [-18.95, 3.88]
Scenario 4 (Landing page ad only)	0%	12.04% [3.18, 31.41]	-10.36% [-23.91, -3.08]
Best	2.81 [-0.48, 6.22]	68.97% [16.49, 184.87]	-37.66% [-64.90, -14.16]

The table shows market outcomes under different scenarios relative to Scenario 1 (business-as-usual). 95% confidence intervals, shown in square brackets, are based on the 2.5th and 97.5th percentiles of the bootstrap distribution.